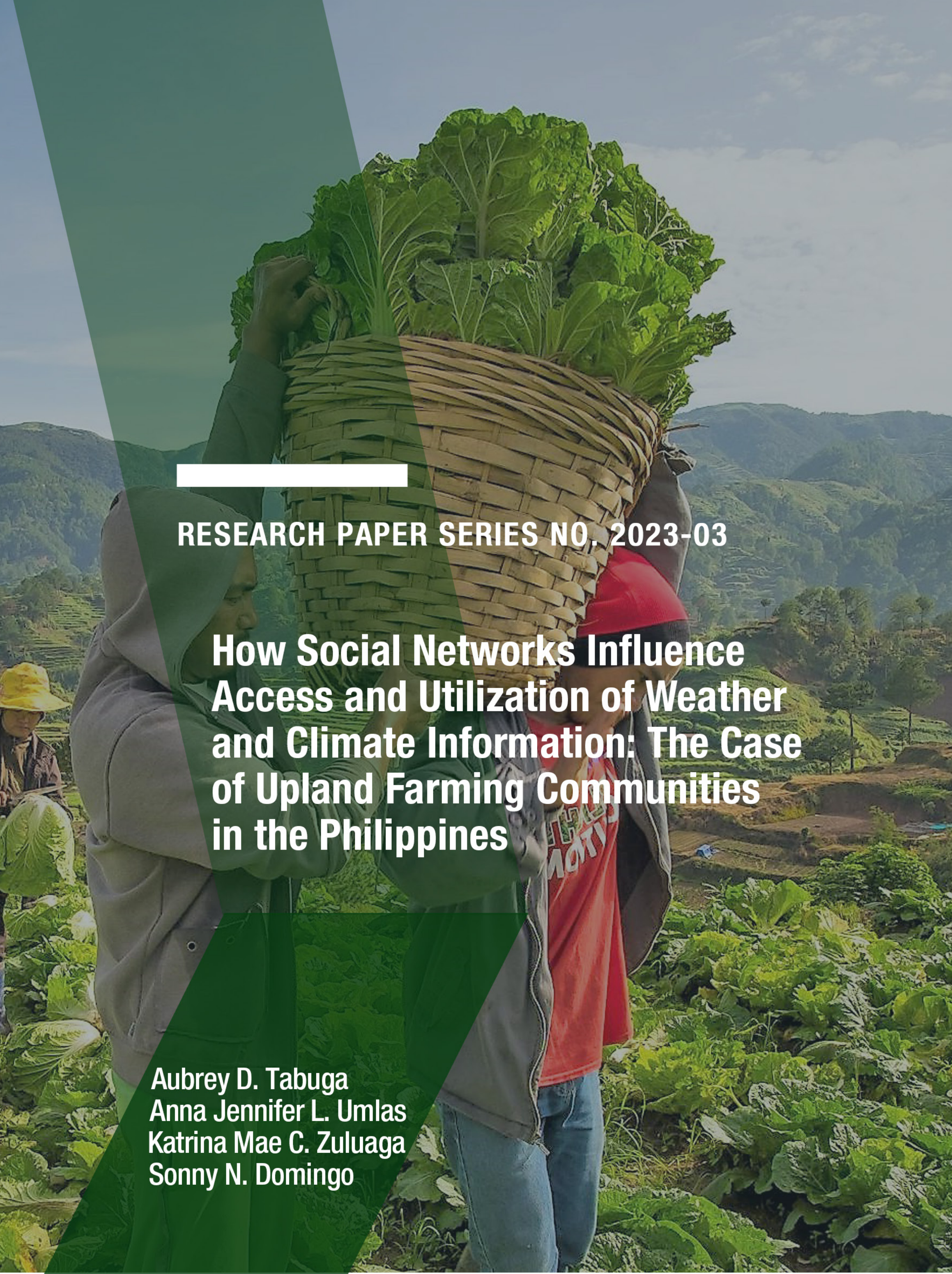

RESEARCH PAPER SERIES NO. 2023-03

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Surian sa mga Pag-aaral Pangkaunlaran ng Pilipinas

Published by
Philippine Institute for Development Studies

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ISSN 1908-3297
ISSN 2508-0830 (electronic)
RP 08-23-600

Cover photo from: https://www.da.gov.ph/lgus-buy-p1-58-billion-worth-of-farmers-produce

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Table of Contents

List of Tables, Figures, and Annexes

Table

Figure

Annex Table

List of Acronyms

AEW	agricultural extension worker
CBMS	Community-Based Monitoring System
ENSO	El Niño Southern Oscillation
FWFA	Farm Weather Forecast Advisory
GMI	Generalized Monsoon Indices
IEC	information, education, and communication
JICA	Japan International Cooperation Agency
km	kilometer
LGU	local government unit
PAGASA	Philippine Atmospheric, Geophysical and Astronomical Services Administration
PAR	Philippine Area of Responsibility
PCA	principal components analysis
RCP	Representative Concentration Pathways
SMS	short message service
SNA	social network analysis
TC	tropical cyclone
TCWA	Tropical Cyclone Warning Advisories
TV	television
WCI	weather and climate information
YMI	Yield Mean Indices

Acknowledgment

We would like to acknowledge the invaluable assistance of our partners from the Benguet State University in the data collection for this study; the Atok Municipal Agricultural Office and local farmers for their kind reception and cooperation; our colleagues from the Philippine Institute for Development Studies; and our partners from the University of the Philippines Los Baños and the Australian Centre for International Agricultural Research for their support. This research project received funding support from the South Australian Research and Development Institute.

Abstract

Social norms and structures are vital factors that shape people's behavior and attitudes. Therefore, analyzing such underlying forces in creating strategies to influence behavior and activities is useful. Agricultural extension services, such as information dissemination and farmers' training, are some of the interventions that can benefit from such analyses, especially within a context of limited human and financial resources. The lessons learned from analyzing social networks and norms can be used to identify potential local knowledge and information disseminators, thereby aiding the extension services. It also helps in formulating more contextualized approaches to reach the underserved and hard-to-reach areas. Applying this approach, this study used the case of a remote upland area in Atok, Benguet, a major vegetable producer. A social network analysis was used to develop insights for designing more effective extension strategies. The results show that interventions like information and education campaigns can be improved by acknowledging the nuances in social relation structures.

Introduction

There is an increasing need to understand the role of networks in people's activities and behaviors. The prevailing way of thought is that these networks have certain characteristics and structures that reflect norms that must be examined if one seeks to influence how people act or behave. For instance, program implementers can take advantage of existing social structures for more efficient dissemination of information and delivery of programs and services, especially when faced with limited resources and workforce. In agricultural communities vulnerable to natural calamities and sudden weather changes, like the Philippines, accessing and utilizing up-to-date weather and climate information is important in managing risks. It is, therefore, important to examine farming households' ability to access and use such information, more so for upland farmers from Benguet Province whose products are sensitive to the amount of rainfall but with limited access to the internet and reliable phone service. In such rural and remote areas, people tend to rely on their personal networks for support and information when needed. This study is about the importance of social networks in accessing and utilizing weather and climate information.

Social networks vary—from kinship to friendship ties and information networks to mere acquaintances to farmers' organizations and other aggregations and linkages to trading/marketing networks and extension workers. Knowing how these networks are structured enables the use of information about that structure for practical purposes. For instance, gathering many smallholder farmers to educate them on the merits of utilizing weather and climate information in their farm-related decisions may be costly from the administrative side. However, there may already be a viable system of communication and interaction in place dictated by social norms in the communities that agricultural extensions and other program implementers can leverage so that efforts meant to disseminate information can be made more manageable yet more effective. In networks with many components or unlinked clusters, identifying the central members in each component who are more likely to influence their network members is essential. These "central" members who can act as hubs can become easy candidates for program beneficiaries because there is an expectation that they can disseminate the knowledge to their circles more efficiently. In other places with more diffused network structure, getting the information to as many members as possible may be more challenging, and a different approach can be designed.

Designing a program approach in this manner is crucial given Benguet's very small number of agricultural extension workers (AEWs)—134 serving 84,087 farmers and fisherfolk. In a workshop on the barriers and opportunities in accessing and utilizing weather and climate information, some participants noted that effectively disseminating information to farmers is a key challenge. Apart from sharing information, there is also the issue of motivating farmers to utilize such information in their farm decisions. Given the AEW-to-farmer ratio of 1:627 in Benguet, it is imperative to explore effective strategies for engaging with farmers in the area. The workshop was held on July 23, 2019, and participated by municipal agricultural officers and disaster risk reduction and management staff of local government units (LGUs) in Benguet.

The role of social networks, particularly in a developing country, is important because access to government services and information, such as weather and climate services and adaptation practices, is limited. The social capital entrenched in a community can be tapped to disseminate information effectively. Many agricultural development projects target key farmers in the hope that they spread the information and influence adaptation practices of their peers and the larger population. Nonetheless, understanding the network's characteristics is a fundamental step in devising interventions for the efficient dissemination of information, reaching target beneficiaries, and ensuring the inclusion of vulnerable sectors.

To ground the analysis, it is helpful to understand how social networks are observed and mapped in different scenarios. In particular, it is helpful to look at the attributes such networks may have; how these networks are compared to each other, if at all; and what characteristics central nodes may have in similar scenarios. While fewer studies discuss this in the context of the spread and uptake of weather and climate information, many others discuss this, considering the adoption of agricultural technologies.

Many studies use network surveys and open-ended interviews to explore and describe a social network at its core. For instance, Nidumolu et al. (2020) surveyed 125 of 270 marginalized farming households in an Indian village. Each respondent was asked to nominate up to five people they would go to for advice. This open-ended interview approach and subsequent semistructured interviews led to a description of the network wherein village knowledge centers, extension workers, and farmer producer companies had a high in-degree of centrality. Their results also tackled networks for seasonal climate forecasts and suggested that these should be distributed through venues that farmers already use, such as farmer meetings and field days. On the other hand, Spielman et al. (2010) used focus group discussions and key informant interviews in 10 purposively selected study sites in Ethiopia to build a network map of rural innovation systems. He found that extension workers and public administration are instrumental in agricultural innovation in the area compared to private companies and market mechanisms.

Meanwhile, Wood et al. (2014) experimented with pastoral farmers in New Zealand to investigate farmer networks and the facilitation of information. They conducted network surveys to identify the persons farmers shared their knowledge with before and after an experiment. In addition, open interviews supplemented the discussion by determining the significance of these contacts. Results of the study showed that farmers discussed the experiment with their contacts, most of whom are also farmers. Moreover, farmers with dense connections and the same occupation-related contacts grew networks more than farmers with loosely connected networks and varied occupations. The discussion shows that farmers value knowledge delivered in person rather than roles, primarily contacting fellow farmers and seeking information from farmers with similar farms and experiences (social homophily). The study also highlights that communication about new agricultural knowledge is likely to happen in day-to-day interactions or socializations rather than in organized meetings. As such, it is important to include the participation of central actors in generating knowledge.

Fewer studies employ one or a blend of face-to-face interviews, experiments, and econometric analysis to evaluate a community's social network. Beamann and Dillon (2018) fully enumerated the household heads and household members in 52 villages in Mali, where there was an average of 35 households per village. They asked the community who they speak to about farming information (primarily pointers on agricultural practices) to map networks and find measures of degree and centrality. In the experiment phase, the researchers conducted training on composting with farmers with either a high degree or betweenness.

They furnished these farmers with placards on composting to distribute to whomever they wished. All farmers were tested on composting later on to assess the spread of information (a nonrival good). They were also asked if they received the informational placard (a substitute for a rival good, like farming inputs). Econometric analysis was then used to determine the relationship between outcomes (receiving a calendar and having a high score on the composting test), an individual's distance from the closest information source, and the relationship between outcomes targeting nodes with a high degree and betweenness. Hoang et al. (2006), on the other hand, used semi-structured interviews for 73 out of 82 households in Pieng Lieng, Vietnam, to ask who talks to whom (discussion network), who asks who for advice (advice network), and who follows whose advice (action networks). They followed up with in-depth interviews with key informants to understand connections between villagers and formal institutions and what the role of these institutions and extensions has been thus far. A previous survey had also already yielded the socioeconomic data of the residents. The results were processed as matrices in UCINet, a software for analyzing social network data, and modeled in Krackplot. The study used factorial correspondence analysis, cross tables, and chi-square distance tests to understand the relations among discrete variables.

The results of these studies give useful insights into the structure and composition of farmers' networks. For instance, Ramirez (2013) found kin and fellow farmers as the main sources of adaptation information in a farmer's social network, citing trust as a significant reason farmers rely more on each other than outside information sources. Similarly, a study by Nidumolu et al. (2020) found that information-sharing mechanisms in India include farmer relationships and formal and informal institutions. Institutional information sources with a high in-degree of centrality were village knowledge centers, cooperative representatives, and government and private extension workers, while weaker ties were to shop owners and government officials.

The composition and structure of farmers' information networks also vary by gender. Cadger et al. (2016) found that women farmers have smaller networks than male farmers. Female farmers also had fewer network connections with individuals from other communities. In Beaman and Dillon (2018), men were more likely to receive information and farming outputs than women. Women in the study had 63 percent fewer contacts and were less central in the village. In villages where information was first targeted to more central nodes to disseminate, women also had significantly lower knowledge than when the information was given to random nodes. Hoang et al. (2006) also corroborated that while targeting central nodes to disseminate information is sufficient to reach a broad circle, it may not be enough to reach nodes on the periphery, like women.

On the other hand, influence within a social network seems tied to individual characteristics such as educational achievement and access to other important resources. Studies of a village in Northern Vietnam differentiated between discussion, advice, and action networks in the community. These studies found that while discussion networks are fairly random, villagers approach village heads, identified opinion leaders, and better-educated individuals for guidance. Greater influence in the community is linked to positions in local government, which, in turn, is linked to larger kin networks, greater education, greater access, and more frequent visits from extension workers. Interviews with villagers revealed, however, that while these individuals were central to the network, they were not necessarily good farmers and would also not necessarily be the best at extension work and disseminating information beyond a broad circle. Thus, in stark contrast to the advice networks, action networks (i.e., networks of those whose advice they follow) revolved primarily around kin, who villagers see as having their best interests in mind (Hoang et al. 2006).

Social networks also have impacts on extension activities and farmer training. Pratiwi and Suzuki (2017) described how farmers with more friends within a training group are more likely to score higher on end-of-training examinations. These results imply that farmers' knowledge-seeking behaviors are positively related to the size of their network. Furthermore, farmers who are more central in their network also exhibit higher test scores, likely associated with their outside-of-classroom ability to coordinate resources and problem-solving activities effectively. On the other hand, the study found that advice networks (networks with extension workers as opposed to only peers) may be detrimental to farmers' knowledge depending on the crop grown. For growers of an established crop like coffee in Indonesia, larger advice networks have a significant positive impact on end-of-training test scores. In contrast, this effect does not hold true for cacao growers. This distinction is probably due to the quality of advice available to relatively younger farmers and extension workers in a newer field.

Other studies showed that beyond pure social ties, an individual's actions (e.g., choosing which crop to grow) could also impact adoption decisions. In Villanueva et al. (2016), larger farmer networks are associated with growing more crops, having more land, and, subsequently, more yield and economic value for crops sold. Farmers with larger networks had also diversified into improved crops and crop varieties. Cadger et al. (2016) also found that types of crops varied with the size of knowledge networks.

Wossen et al. (2013) also reported that distance from a technology adopter determines an individual's adoption behavior. Having larger networks with more relatives, friends, and neighbors, as well as the distance between network members and the physical location of plots near adopters' farms, increases the chances of adopting new farming and resource management practices. Proximate social distance from the giver also impacts the distribution of rival goods, such as farming inputs. However, Beaman and Dillon (2018) found the effect was not as pronounced with nonrival goods such as information.

Overall, a network's size and a farmer's position in it depend on participation in development and training, cultivated crops, and individual characteristics such as gender and educational achievement. Social ties, physical proximity, and the involvement of government and institutional actors also shape the interactions of agricultural stakeholders in the community and form important communication mechanisms between nodes.

Moving forward, there are diverse approaches to leverage this information. A robust social network would aid greatly in bringing climate-resilient agriculture initiatives up to scale. Beaman and Dillon (2018) found that farming information on a placard, in this case, a calendar for display in homes in Mali, was an effective way to distribute information in some cases. This is especially so when the calendars are given to random nodes in the community to distribute compared to tapping highly central individuals, who tend to miss out on peripheral nodes. In a study in Ghana, researchers also identified a gap between information access and use for smallholder cocoa farmers. They also find that agricultural extension could benefit from taking advantage of the spread of information from farmer to farmer and recommend localizing, laymanizing, and framing information on adaptive techniques in a way that farmers can understand (Maguire-Rajpaul et al. 2020).

On the other hand, technological adaptation includes the widespread adoption of cell phones among African agriculture entrepreneurs. This facilitates long-distance interaction and the development of weaker social ties that provide access to new resources and opportunities (Mehta et al. 2011). In the case of India, many private and public Information Communication Technologies are being leveraged to disseminate agricultural information. E-Choupal, for instance, is a platform that acts as a market channel that provides transparent pricing and thus eliminates intermediaries, while e-Sagu is a personalized extension advice platform. However, reports on the usefulness of these and many other platforms note that impact could be improved if farmers' awareness and capacity are built to use them better. At the same time, the lack of supporting infrastructure is also addressed (Kukreja and Chakrabarti 2013).

These studies illustrate the importance of social networks in agricultural production and technology adoption. But no one seems to have examined the influence of social networks on farmers' access to weather and climate information in the context of high susceptibility to weather and climate changes. This study fills this gap by examining the case of farming households in three upland communities in one of the country's key vegetable-producing regions.

The main goal is to inform programs and policies relating to local strategies for information dissemination and to improve connections among farmers, extension workers, and knowledge producers. Specifically, it seeks to (1) characterize the social, economic, and information networks in the study areas; (2) examine any variation in the structure of different types of information networks; (3) analyze any association between network connectivity and farmers' ability to access and utilize weather and climate information; and (4) recommend improvements in the design of information and education campaign and related interventions of AEWs in the area.

The following are the research questions explored in this study:

a. What is the structure of the social networks of farmers and/or households in the selected areas? Which households in the community are the central actors in the networks and are most likely to be the best disseminators of information? Who in the periphery may be reached through a different approach?

b. Are there different networks for different types of weather and climate information?
c. How is connectivity correlated with access and utilization of weather and climate information?
d. What are the lessons/insights learned from this exercise that can inform the design of information and education campaigns of extension workers and other local programs?

Weather and Climate Information in Farm Decisions

Much of the weather and climate information referred to in this study are those from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA), the country's lead government agency mandated to provide "adequate, up-to-date data, and timely information on atmospheric, astronomical, and other weather-related phenomena using the advances achieved in the realm of science" (PAGASA n.d.-a). This mandate separates PAGASA from other providers of weather and climate information. Indigenous weather forecast practices and non-PAGASA sources of weather and climate are also included in the study, although greater emphasis is given to PAGASA products.

PAGASA provides the following weather and climate products, which are grouped based on the period covered (see Annex Table 1 for the list of PAGASA products):

a. Warnings refer to the information reported hours before the occurrence of the actual weather event.
b. Weather forecast refers to the state of the atmosphere (or the weather situation) at a particular location over a short period.
c. Climate outlooks and advisories describe information for a "season" that may range from one month to one year.
d. Climate projections provide information on the likelihood of something happening in climate for several decades or centuries.

According to the Municipal Agricultural Office of Atok, most smallholder farmers in the municipality depend on rainfall as the primary source of irrigation. There are supplemental sources of irrigation, such as water delivery services and the use of water pumps. However, these are costly to the farmer, and in the case of water pumps for supplemental irrigation, the water sources also depend on rainfall. Therefore, rainfall information is crucial to various farming decisions. For example, information about the onset of rain is important since it determines the start of the planting period. If the farmer plants and there is insufficient rainfall, the crop will not sprout. If there is too much rainfall, the seeds will be washed away. Other farm decisions affected by rainfall are crop choice and supplemental irrigation. Benguet has a Type I climate wherein there are two pronounced seasons, dry season from November to April and wet for the rest of the year. According to the municipal agriculturist, the wet and dry season in Atok is no longer distinct, so it is more difficult for farmers to plan their activities.

In addition to rainfall information, typhoon information is also significant to farmers because it can cause surface runoff and damage to farms due to the municipality's mountainous terrain. The terrain also causes varying microclimatic conditions in the area. Hence, it is also important to consider indigenous forecast methods for rainfall and typhoon.

Indigenous information on rainfall refers to the set of traditional beliefs about obvious, observable conditions in nature that forecast the arrival of rainfall well ahead of time. For instance, the farmers in La Trinidad and Atok believe that the arrival of the *siyet* or *indokit* bird in December signifies the beginning of the cold season, characterized by scattered showers and gusty winds.

Indigenous information on typhoons similarly refers to the set of traditional beliefs about obvious, observable phenomena in nature that forecast the arrival of typhoons. Farmers in La Trinidad and Atok believe, in this case, that the arrival of another migratory bird killing heralds the start of the dry season; one day and one night after the bird's appearance, a typhoon will usually follow. Farmers stated, however, that the siyet and killing birds are becoming less accurate signs to predict the weather.

PAGASA utilizes various venues to disseminate weather and climate information. The foremost source is the PAGASA website (https://pagasa.dost.gov.ph). The agency also has official social media channels such as Twitter, YouTube, and Facebook and holds periodic climate forums, which can be accessed on their official accounts. In case of extreme weather events such as typhoons and extreme droughts such as El Niño, PAGASA directly coordinates with the National Disaster Risk Reduction and Management Council, which then sends the information and warns the public via short message service (SMS).

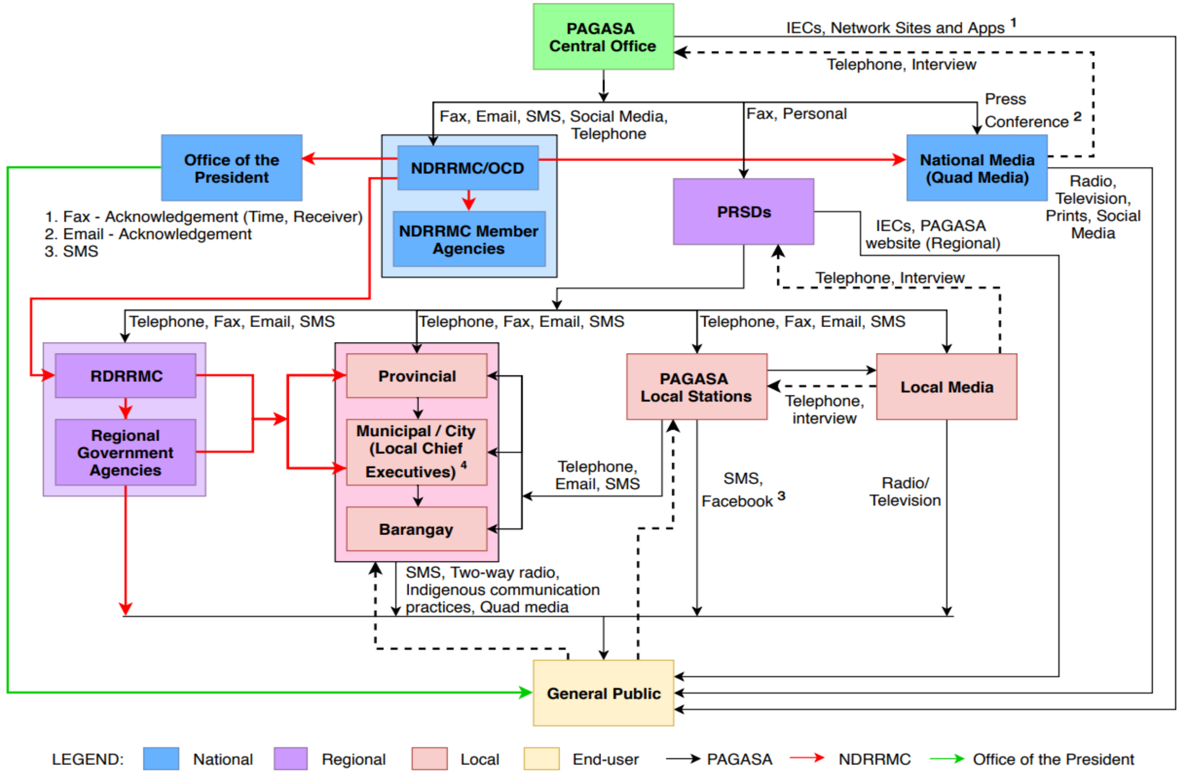
There are also initiatives from PAGASA to make weather and climate information more accessible and user-friendly to the public in general. In 2016, PAGASA launched a new mobile application named DOST-PAGASA. The mobile application contains weather and climate information such as weather bulletins, flood information, tropical cyclone warnings, rainfall, and thunderstorm warnings[1] (JICA n.d.). The state weather bureau also has another mobile application *Payong* PAGASA, launched in 2018. It features information on daily monitoring of rainfall and temperature, monthly climate assessment and outlook, farm weather forecasts and advisory, 10-day regional agri-weather information, and 10-day weather outlook, among others. PAGASA also developed and used various warning systems to make it easier for the public to understand climate and weather information and its possible impact. Moreover, they have created simplified information and educational materials about weather events such as tropical cyclone warnings, information on floods, La Niña and El Niño, and rainfall warnings. It also features its mascot, aptly named "Ella the Umbrella".

Figure 1 shows the information dissemination flow of weather warnings and forecasts. The PAGASA central office directly communicates with the public through information, education, and communication (IEC) materials, the PAGASA mobile app, and its website and social media accounts. They also disseminate information to key government agencies such as the National Disaster Risk Reduction and Management Council, PAGASA regional offices, and national media outlets.

Figure 2 shows the information dissemination flow of seasonal climate forecasts. Like weather warnings and forecasts, PAGASA central office communicates directly with the public through IECs, the PAGASA mobile app, and its website and social media accounts. This information is also distributed using quad media. PAGASA officials and staff also attend hearings at the House of Representatives or Senate committees as resource persons, participate in technical working groups related to planning and mitigation, and conduct National Climate Outlook Forum for various stakeholders.

[1] https://www.rappler.com/environment/disasters/136568-pagasa-unveils-smartphone-app (accessed on May 29, 2023).

Figure 1. Information dissemination flow of weather warnings and forecasts



PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration; IEC = information, education, and communication; NDRRMC = National Disaster Risk Reduction and Management Council; OCD = Office of Civil Defense; PRSD = PAGASA Regional Services Division; RDRRMC = Regional Disaster Risk Reduction and Management Council; SMS = short message service

[1] IECs, PAGASA website, PAGASA mobile app, PAGASA Common Alerting Protocol through Google Public Alert and PAGASA social media accounts (Facebook, Twitter, Youtube, and Viber)

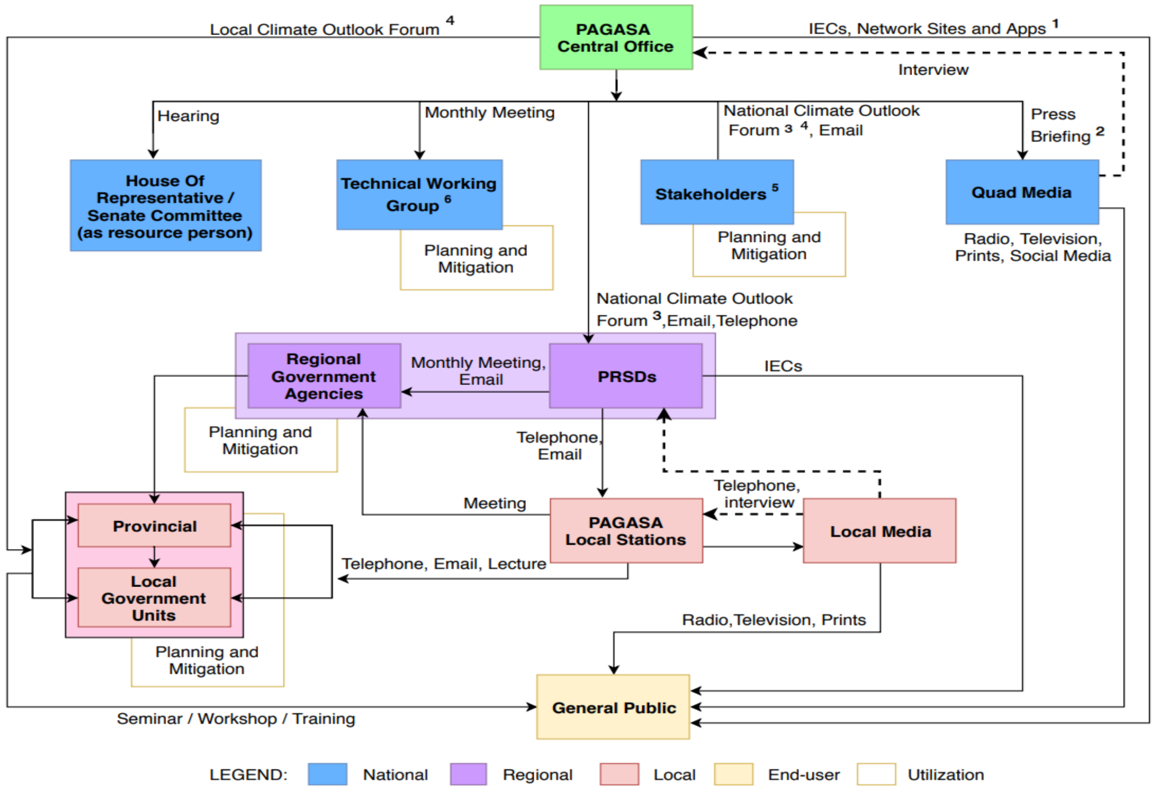
[2] in the event of typhoon passage

[3] weather information written in dialect

[4] As soon as the DRRs of the LGUs receive a weather bulletin/advisory from PAGASA, the Mayor will form a meeting as head of the municipal/city council. The Mayor will then also convene and give information to barangay leaders and city level leaders/officials.

Source: PAGASA (n.d.-b)

Figure 2. Information dissemination flow of seasonal climate forecasts



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[1] IECs, PAGASA website, Payong PAGASA mobile app, and PAGASA social media accounts (Facebook, Twitter, and Youtube)

[2] during ENSO and other extreme events

[3] live streaming via Youtube/Facebook live

[4] physical attendance

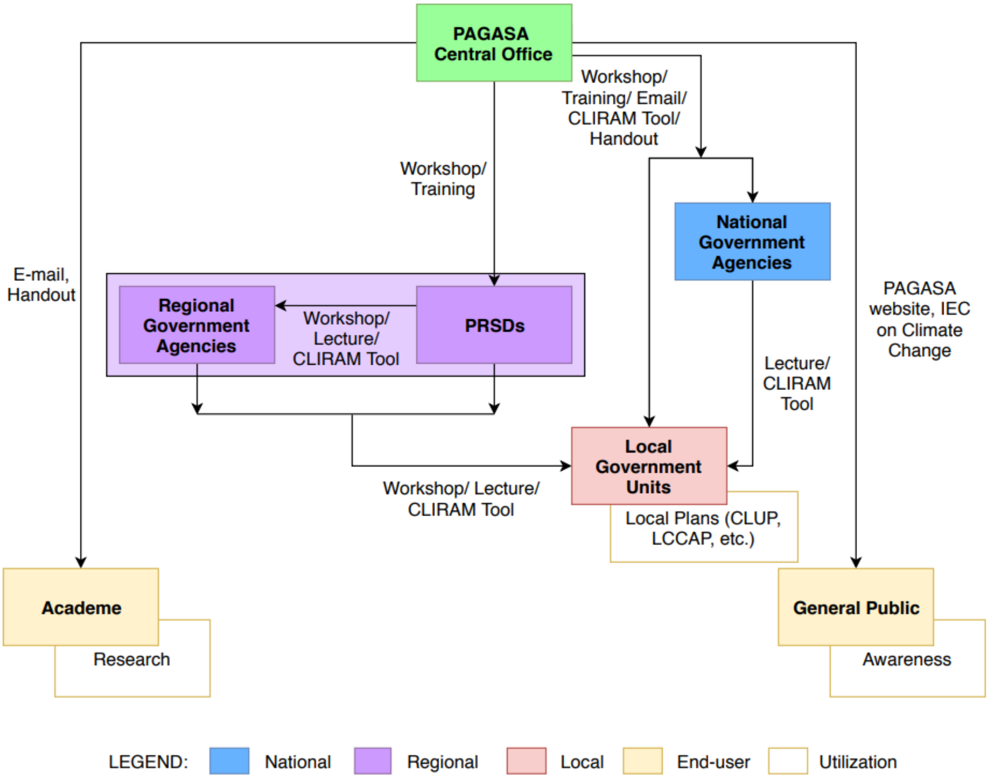
[5] NGAs, attached agencies, NGOs, GOCCs, academe, business and private sectors

[6] Technical Working Group on (a) Angat Dam Operation and Management, (b) Food Security committee, (c) PCAF committee, and (d) El Niño Task Force

Source: PAGASA (n.d.-b)

Figure 3 shows the information flow for climate projections. The IEC materials on climate change are available on the PAGASA website. The agency also conducts workshops with national, regional, and local government agencies to aid them in crafting their local plans.

Figure 3. Information dissemination flow of climate projections



PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration; IEC = information, education, and communication; PRSD = PAGASA Regional Services Division; CLIRAM = Climate Information Risk Analysis Matrix; CLUP = comprehensive land use plan; LCCAP = local climate change action plan
Source: PAGASA (n.d.-b)

Despite these efforts and initiatives, PAGASA is still not the main source of weather and climate information and has limited reach to the farmers. The identified barriers to access and utilization of weather and climate data from the state weather bureau are the limited internet access of farmers and the complexity of the information, making it difficult for farmers to understand them.

AEWs can play a key role in bridging PAGASA and smallholder farmers, as they are aware of the local conditions faced by the farmers and knowledgeable of the impact of weather and climate on farming decisions. It is also easier and more practical to train AEWs than farmers in understanding weather and climate information since training the latter requires a huge amount of resources due to their vast number and various backgrounds and skills. Hence, AEWs are strategically positioned to disseminate weather and climate information and make the information useful to the farmers.

Data and Methodology

Survey data

This study uses primary data collected from 239 households in three *sitios* (Proper Paoay in Barangay Paoay and sitios Tulodan and Macbas in Barangay Cattubo) in Atok, Benguet. A sitio (Spanish for "site") is a subdivision of a barangay in the Philippines. The primary data-gathering activities for this study were conducted from October 2019 to the first week of December 2019 using a structured survey instrument administered through face-to-face conversation/survey. All data were recorded in a tablet-based platform. The data collection process for the survey, which included social networks, is relatively expensive and arduous. As a requirement, the study must select areas with existing census data of all households and very low constraints to complete the enumeration. Ideally, the study areas should have enough farm households for the crop of interest, and the enumeration of kinship and friendship ties (and other links) is politically feasible. Linkages or connections data are highly confidential and sensitive information; some people may not be very keen to disclose this information. Hence, the caveat is that although there is a complete enumeration, there is an assumption that the resulting data do not perfectly capture all the networks. Another requirement for data gathering is for LGUs and barangay officials of the study areas to support the field operation fully.

This study selected three sites in Atok, Benguet, to make the comparison possible. One criterion is that these sites should vary in geography or location. The other criteria require the feasibility of full enumeration and the production of crops of interest (cabbage, carrot, and potato) in these areas. The PIDS team conducted site visits in Atok, Benguet, and held discussions with Benguet State University, the partner university, the municipal agricultural officer, and selected barangay officials on April 15, 2019. These consultations were important since they were more aware of the local conditions of Atok, the study site.

The municipality of Atok is in the province of Benguet and is approximately 300 km north of Manila. It has a land area of 22,385.4958 hectares. It is centrally located with the municipalities of Kibungan and Buguias on the north, Kabayan and Bokod on the east, Kapangan on the west, and Tublay on the south (see Figure 4). It is upland and produces high-value crops such as cabbages, potatoes, carrots, and cut flowers. Two-thirds of the land area has a 40–60 percent slope and is characterized as hilly to mountainous, while the remaining one-third has 60 percent above the slope and is characterized as rugged mountain areas. Because of the landscape, the municipality develops varying microclimatic conditions, and hence the role of weather and climate information is valuable to the smallholder farmers. It also emphasizes the role and the need for AEWs in effectively delivering weather and climate information to the farmers, among others, to help address and prepare against the adverse impacts of extreme weather and climate events. Most farmers depend on rainfall as a primary source of irrigation. Although the conditions in Atok make an interesting case for social network analysis on access and use of weather and climate information, it makes data collection more strenuous because of the distribution and location of households and the knowledge of local partners more important.

Based on consultations with the Atok Municipal Agricultural Office, barangay representatives of Barangay Paoay and Cattubo, and partners from the Benguet State University, three sites for the survey in Atok were identified. A full enumeration of a barangay was not feasible because of the large population and transportation and budget constraints. Barangay Paoay was not considered initially because of respondent fatigue in the area and the huge number of households. The other barangays were too far from the center, and households were quite dispersed. Hence, the probability of a complete enumeration is impractical. Because of these challenges, and to make the full enumeration feasible, the geographical unit was reduced to sitios.

According to the municipal agricultural office of Atok, Barangay Paoay and Cattubo are major producers of cabbage, carrots, and potatoes. The sites chosen were sitios Proper Paoay in Barangay Paoay and sitios Tulodan and Macbas in Barangay Cattubo. Barangays Paoay and Cattubo are two of the most populous barangays in Atok (see Table 1). These sites comprise 315 households (i.e., 89 in Macbas, 94 in Tulodan, and 132 in Proper Paoay). Thus, the primary data collection covered 315 households. All the sites are communities with 70–80 percent rain-fed vegetable farms but with arguably varied potential for the spread of information. While Proper Paoay is a denser sitio and nearer to the municipality, households in Macbas and Tulodan are more dispersed and located far away from the center of the barangay and municipality. Each sitio also had an available household listing that the researchers obtained from the LGU. Overall, these sitios are well-delineated and have geographies that allow for complete enumerations. Although comparable, they possess unique characteristics that could make drawing parallels between respective networks more interesting.

Figure 4. Map of Benguet Province and its municipalities

Source: Google (n.d.)

Table 1. Population of Atok by barangay, 2015

Barangay	Number of Households in 2015	Number of Respondents in the ACIAR 2018 Survey	Population in 2015
Abiang	406	29	1,757
Caliking	708	31	3,402
Cattubo	601	64	2,482
Naguey	346	0	1,723
Paoay	1,069	64	4,395
Pasdong	279	0	1,193
Poblacion	454	13	2,077
Topdac	515	0	2,639

Source: Authors' computations based on primary data and PSA (2015)

There were some notable difficulties during the field survey. Before the start of the survey operations, the project team collected household lists per sitio from the barangay. These lists were used as the basis of the household survey. The respondents were all farming and nonfarming households living in sitios Proper Paoay in Barangay Paoay and Tulodan and Macbas in Barangay Cattubo. Based on the barangay lists, the total number of interviews was 315 households. However, only 239 interviews were completed (Table 2). The survey team faced difficulties in doing the household interviews.

Table 2. Number of completed interviews

Barangay and Sitio	Frequency	Percent	Cumulative
Sitio Proper Paoay, Barangay Paoay	119.00	49.79	49.79
Sitio Toludan, Barangay Cattubo	74.00	30.96	80.75
Sitio Macbas, Barangay Cattubo	46.00	19.25	100.00
Total	239.00	100.00	

Source: Authors' calculations based on primary data

Some respondents were excluded from the survey since they no longer reside in the study sites. It was also difficult to schedule and conduct the interviews because of the farmer's schedule. Most of them leave their residence early morning to tend to their farm and return home in the afternoon before sunset. Hence, the enumerators had a small window to conduct the interviews and, at most, could only do three interviews in a day. Houses were also spread over wide areas, and some were in uphill places that could only be reached by walking. Moreover, transportation was limited within a sitio.

Social network data

This study collected various types of networks, including the quality of the relations. These relations contain social capital that people can convert into other forms of capital. Social capital represents the actual or virtual resources people have accumulated through their "more or less institutionalized relationships of mutual acquaintance and recognition" (Bourdieu and Wacquant, 1992, p.119).

Networks can be role-based, such as kinship (i.e., relations by blood and marriage) and friendship ties. It is essential to capture these relations as they may be considered the intrinsic source of people's social capital in a community. They may not always share information and other resources, but they are highly likely to connect as needed occasionally. In addition to kinship and friendship ties, this study collected data on information networks, such as, but not limited to, weather and climate information networks. However, obtaining information networks related to weather and climate information alone may not suffice to capture an actor's extent of connectivity with other nodes, which is useful for designing future information and education campaign strategies. Suppose the information being shared in a weather and climate information network pertains to recent or current weather and climate information (which is less prone to recall error). In that case, the network data collected will likely reflect the current or recent network structure. Although it would be useful in explaining the constraints and opportunities for accessing and utilizing weather and climate information in recent times, it may lose some relevance in informing future strategies. The idea is to understand the structure of the social networks of farmers and households in the community (i.e., networks that are measured exhaustively or in different ways). This way, the generated knowledge is more likely to reflect the true networks and can be utilized for future program design purposes, not just to explain the current situation. Hence, besides the abovementioned role-based networks and information networks, the study also collected farm inputs and advice networks.

This study gathered data on the social networks of the household head and spouse. The social relations of each of these individuals were collected—starting from kin, then friends, then economic contacts, then individuals with whom they share information and resources. The unit of analysis is both at the household and individual farmer levels. Networks of focus are those situated within the selected communities. If the individuals/households have key contacts outside the community, such as extension workers, traders, marketing agents, and external suppliers who play an important role in their farming activities, these were likewise included in the network data collection. Details on the data collection process are discussed in the succeeding sub-section.

To obtain social relations data, the survey enumerator asked the respondents (household head and spouse in each household) to identify a maximum of 50 social (kinship and friendship) contacts and all direct contacts related to weather and climate information within the sitio of interest. The information on social networks that were gathered was precise. For example, the respondent was asked to identify whether the social contact was a parent, a cousin, an aunt, or an uncle. Table 3 shows the social links that were collected through the survey. The variables of interest—weather and climate information—were segregated based on the validation/technical analysis outcome conducted with PAGASA, local officials, and AEWs.

In collecting social network data, the progression of the survey interview started with respondents being asked to identify all friends and neighbors, followed by work-related contact, and then kin. The enumerator then asked respondents whether they obtained or shared weather and climate information, have established links involving farm advice and farm inputs, and credit with the identified social relations. Since there may be links outside the person's social ties, respondents were also asked for other contacts (outside social relations) with whom they interacted concerning the abovementioned variables of interest (e.g., whom they obtain and share weather and climate information, farm inputs or advice, and credit).

The survey focused on the internal networks (i.e., people living within the same sitio as the respondent). Limiting the network to within-sitio contacts rendered the survey operation more feasible. External networks were only collected when the respondent identified significant contacts outside the sitio. Furthermore, the focus on within-sitio networks rests on the assumption that people in more geographically isolated areas (e.g., those

Table 3. Social relations gathered

Friends and Neighbors	Work-related Contacts in the Past 3 Years	Kin	Weather and Climate Information Networks	Other Social Networks
Close friends	Employer	Parent-child	Heavy rainfall and thunderstorm alerts	Farm advice
Childhood friends	Worker	Siblings	Tropical cyclone warnings/typhoon	Farm inputs
Neighbors	Co-worker, colleague	Children	Daily weather forecasts	Credit links
Kailian	Hired labor	Aunts/uncles	Bi-weekly and weekly forecasts	Health information
Churchmate	*Suplay*/supplier	Cousins	Two-to-six-month forecasts	
	Creditor	Niece, nephew	ENSO forecasts, El Niño, La Niña	
	Trader	Grandchildren	Narratives	
	Disposer	In-laws	Climate projections	
	Trucker		Indigenous forecasting information	
	Private technician		Non-PAGASA information	

ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' compilation based on primary data

in Atok with limited access to information due to poor mobile phone signal and limited mobility) depend more on proximate contacts and social relations.

Initially, the study required a full enumeration of units within a geographically bounded community, in this case, a sitio (sub-unit within a barangay). Suppose the enumeration is partial (i.e., it does not cover the community as a whole or sitio). In that case, the parameters may not fully reflect the precise connectedness characteristics of the households in the community. However, not all targeted households were interviewed due to various reasons. Though this presents a limitation, the parameters yielded still constitute 76 percent of the actual network, which is acceptable given the extreme geographical constraints encountered by enumerators.

Also, relations data can be obtained from either side of the link; confirming it from both sides is not required, but the relationship is still considered reciprocal. Since many of the targeted respondents who were excluded were in remote locations, it is highly likely that they are less integrated with the rest of the community. This indicates that the true social cohesion parameters may be lower (i.e., communities are less cohesive) than the ones calculated from the actual data gathered.

Access to weather and climate information

Based on encyclopedia.com, "information access is the ability to identify, retrieve, and use information effectively."[2] The weather and climate information from PAGASA does not necessarily reach the end users, in this case, the farmers. This study examines farmers' access which is narrowly defined as having received, voluntarily or involuntarily, such information through any platform, media, or person (internet, SMS, traditional mass media, or neighbors) in a given time, regardless of the individual's understanding of the information and subsequent choice of whether or not to act on it. Other ways for determining and examining access like level of awareness, whether the person actively searches for such information, the type of information he/she seeks, whether he/she obtains what he/she needs in a timely manner, and the specific sources of weather and climate information were also gathered.

For every category of PAGASA product and indigenous and non-PAGASA weather and climate information sources, the following questions were asked to examine respondents' "access".

1. Have you heard of this type of weather and climate information?
2. If yes, do you feel you need further explanation on this information?
3. Do you actively seek this information for any of your farming decisions?
4. Are you able to access this information when needed? (5-point Likert scale from 1: Always to 5: Never)?
5. What are the sources of this information?

[2] https://www.encyclopedia.com/computing/news-wires-white-papers-and-books/information-access (accessed on July 19, 2021)

Utilization of weather and climate information

Even if farmers can obtain weather and climate information, utilizing this for farm decisionmaking is not guaranteed. In this study, utilization is operationalized as when the weather and climate information affects farmers' farm-related decisions, such as, but not limited to, the timing of planting and harvesting, choice of crops to plant, or whether to invest in supplemental irrigation. An information search by farmers may also supplement this. Actively searching for weather and climate information roughly means the farmer intends to use it in his farming decisions.

1. Do you actively seek this information for any of your farming decisions? (Yes/No)
2. Did you ever use this information for decisionmaking in your farming activities? (Yes/No)
3. From 1–5, how useful do you consider the information?
4. During the last cropping season, did you (or any other member) visit the PAGASA website, including its official social media channels such as Facebook or Youtube, to get information on weather and climate?

Other variables

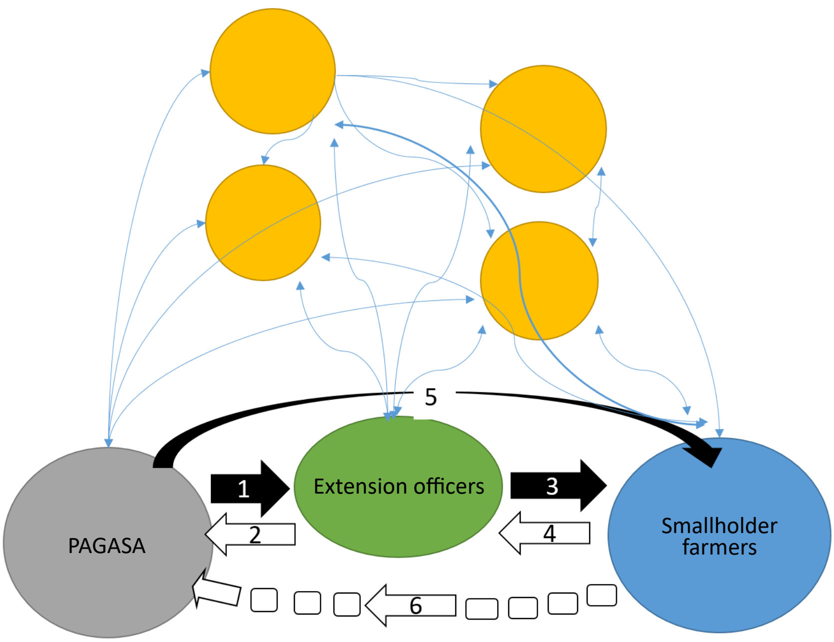
It was also useful to gather data about the respondent's educational attainment, marital status, ethnic group, membership in organizations, primary occupation, farm characteristics, availment of credit, and other individual-level information. Information on whether the individual ever attended farmer field school, local government meetings, and interacted with an AEW in the past was also collected. The survey also collected information on household variables like the number of members and assets (e.g., vehicles, smartphones, tractors). A variable for physical proximity was also included in the survey—the reported physical distance between the household dwellings and the place or venue they frequently visit to meet people—as this can help explain people's ability to reach others. The importance of physical proximity on social influence is highlighted in Meyners et al. (2017), which is assumed to have a great role in the analysis of this paper's chosen context.

Data analyses

This paper used social network analysis (SNA) as the key methodology to examine the role of social networks in accessing and utilizing weather and climate information in selected communities in Atok, Benguet. The SNA is a paradigm that focuses more on relations rather than attributes. It examines the structure of ties among social actors or nodes, which can be persons, homogenous groups, organizations, or nations, and provide a way to make correlations possible.

The proponents of this paradigm note that many constraints and opportunities people face are influenced not necessarily by who they are but by who they are connected with and the structure of their social networks. In Figure 5, although some information can be directly obtained from data sources like PAGASA or extension officers, others can be relayed or disseminated by social relations whom farmers often interact with.

Figure 5. Schematic of agricultural knowledge information system in Benguet and Mindoro



PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' illustration based on primary data

In contagion models, such as those that explain the diffusion of infectious diseases, the higher the network density (i.e., more connections relative to total possible connections), the faster the disease spread rate (Jackson et al. 2007). The theory of social influence also lends insights into examining social networks and their potential influence. This school of thought notes that social influence is a function of social proximity, whether by structural cohesion (i.e., close social relation) or structural equivalence (i.e., having similar attributes or coming from a homogenous group) (see Marsden and Friedkin 1994). Therefore, a more cohesive social network allows for more social influence and greater diffusion of information. Social cohesion is operationally defined as the extent to which community members share resources and trust each other. The objective measure for social cohesion is network density. Individual connectedness or centrality is also important. The well-connected actor or person will likely be the most effective influencer or broker of information and other properties flowing through the network. Network actors with more connections are better positioned to receive and share information than those with very few connections or not connected at all (Banerjee et al. 2013). If one seeks to influence people to use scientific knowledge in their farming, such as weather and climate information from PAGASA, influencing others may be more challenging given a more diffuse network or when he/she has very few connections, all else being equal. On the other hand, a more closely bonded community would be more conducive to knowledge diffusion and social influencing amongst its community members.

The SNA is the most fitting methodology for understanding social networks and their likely influences. Through its meso-level approach, it can enrich individualistic analyses like regression analyses that this paper also uses for more formal analysis of the relationships. SNA also provides a visual representation of the social linkages, a unique way of illustrating and understanding the social network structure. Through this, one can examine the weather and climate information flow among network actors.

The SNA software package, UCINET, was used to yield network parameters such as density (actual ties divided by the total number of possible ties), components (number of distinct clusters), geodesic distance (the length of the shortest path between any pair of network actors), and diameter (the shortest distance between the two most distant actors in the network). At the individual network actor level, it also calculates parameters of connectedness such as degree, betweenness, closeness, two-step reach, and eigenvector centrality, among others. Each parameter measures a specific aspect of connectivity. The degree gives the total number of nodes or actors to which an actor of interest is directly connected. The two-step reach centrality is the number of actors one can reach in two or fewer steps; it provides the extent of an actor's indirect links. Betweenness, meanwhile, is the proportion of pairs of actors in which a particular actor acts as a broker because it lies within their shortest path. Removing an actor with a high betweenness score will likely disrupt communication channels. The eigenvector centrality shows how central an actor's connections are. Closeness centrality measures how close one is to all other actors in the network.

Identifying centrality is essential because it gives a notion of the hubs, the potential influencers, and the bridges that bind communities together (Banerjee et al. 2013). These bridges are also potentially the most effective information disseminators and influencers. If information is coursed through them, they are expected to disseminate it more efficiently. Similarly, this analysis provides the nodes at the periphery (i.e., those least connected to the rest) and their characteristics. These households may benefit from a more direct information dissemination approach because they have fewer connections.

The study provides the network graph for each selected site and by type of network (i.e., social networks, information networks). The network graphs are usually presented at the household level. This means that the total number of nodes is equivalent to the total number of households in the survey. At the time, they were also segregated based on the sex of the identifier such that the paper could show both the male-identified network of households and the female-identified network. Note that the respondents were both household heads and spouses (if any). The network graphs also reflect attributes of actors or households f or more nuanced appreciation. Examples are networks showing households that have ever interacted with an extension worker through node coloring. The node size can also be differentiated based on centrality scores.

It is important to note that this paper does not account for how networks are formed, nor is it about the causal relations between social connectivity and access to information or other outcomes of interest. Thus, all analyses are exploratory and correlational.

Regression analyses

A logit regression analysis was implemented to formally estimate the correlation between connectedness and the variables of interest—access and utilization of weather and climate information. The network parameters calculated for each respondent in the study can be used as explanatory variables in the regression analysis of access and utilization of weather and climate information. For instance, let Y1 denote access and utilization such that Y1=1 if the actor has access and utilizes the information; otherwise, it is zero (0). This demonstrates how the network scores correlate with the probability of getting a positive outcome. The hypothesis that can be tested is that the more (less) connected the household/farmer is, the more (less) likely the household/farmer accesses and utilizes weather and climate information, holding other factors constant. Note that, at the minimum, such analyses are correlational, not causal or attributional. Causal analysis is difficult to implement in this study. A fundamental criticism of using parameters from social network analysis in regression analyses comes from the potential endogeneity issue of networks. That is, networks may have developed from certain activities related to the outcomes. For instance, one who has limited access to some useful information may intentionally link up with a person known to have more connections so that she can obtain the needed information. The dependent variable, having or not having access to the information/knowledge, is influencing the connectedness of the individual—a simultaneity that violates the exogeneity assumption in most regression analyses. Networks, therefore, are unlikely to be exogenous. Blood relations do not have this kind of problem because one cannot self-select himself to the family (i.e., it is a given). However, friendships and acquaintances, economic networks, and organization-related ties are likely to be endogenous.

Results and Discussion

Profile of survey respondents

The average age of the household head surveyed in this study is 43, ranging from 19 to 84 years old. Most (88%) of the household heads are male. Nearly half (46.6%) completed at least high school. All the household heads are members of an organization or beneficiaries of government programs. Almost all (94.1%) heads are engaged in farming, with an average of 17.4 years of farming experience.

Most households have a radio and television (TV), which are important information sources. Seventy-six percent have a basic phone, meaning it can call and text but cannot access the internet, while 69 percent have a smartphone. Internet use is low, with only 36.8 percent reporting having access to it. None of the respondents has a landline. Ownership of means of transportation is limited, with only 15.5 percent owning a motorcycle and 31.8 percent owning other types of motor vehicle.

The importance of social networks manifests in upland households' economic activities. In this survey, households who availed of credit last year reported that the most common sources of credit are relatives and friends, where 42 percent of the 72 respondents confirmed such as their source. In contrast, only 30 percent noted they borrowed from credit cooperatives, 15 percent from disposers, and only 3 percent from banks. In choosing market channels, respondents consider convenience (n=102) as the primary factor, followed by trust in the market channel (n=89), high price or return (n=72), and friendship (n=46).

As farmers, most household heads across all three sitios are involved in growing vegetables, with 196 respondents naming this as their primary farming activity. Other minor farming activities include growing cut flowers, primarily alstroemerias, and cultivating ornamental plants. Vegetable growers across all sitios, on the other hand, reported planting cabbage the most, followed by potatoes and then carrots. Twenty-six percent of the respondents specified cabbage as the crop with the highest contribution to income, followed by potatoes (23%) and carrots (11%). Ten percent of the respondents reported that lettuce and radish contribute the most to their income.

In terms of farm resources, most of the households do not own a water pump (61.09%), tractor (73.64%), and greenhouse (87.45%). The average farm size operated in the previous cropping season is 1.23 hectares. Spring (45.80%), rivers (28.99%), and rain (10.50 %) are the primary sources of farm water. Meanwhile, hose/sprinkler irrigation is the most common form of farm irrigation (57.14%), followed by surface water pumping (13.45%) and private tanks (11.34%). A significant amount of communication may happen through physical interactions, given the poor mobile phone signal in the areas. Also, despite the proliferation of smartphones and computers, 31 percent of households have yet to acquire their first smartphones, and only 7 percent have a computer. None of the respondents have landline phones, although three-quarters have basic mobile phones.

Table 4 shows that many respondents convene in Sayangan (n=152), where the municipal office, public market, and transportation hub are located for errands and other purposes—where they can interact with other people in the area. Other mentioned places are the barangay hall (n=100) and church (n=65).

Other venues of learning and communication exchanges can be through government programs. Attendance in farmer field schools is low at only 22.84 percent. Only 40.17 percent of the households have interacted with a government AEW. The common ways of interaction between the farmer and government AEW are by the AEW visits to the farmer and AEW giving a presentation. On the other hand, attendance in local government meetings is relatively higher compared to farmer field schools. 39.33 percent of the households reported attending a meeting organized by the LGU. These meetings include farm-related seminars (30.13 percent) and disaster-preparedness seminars (11.72 percent). Most of the farmers are also open to adopting new technology. On a scale of 1 to 5, with 1 meaning unlikely and 5 meaning "definitely", the average answer is 3.98.

Table 4. Frequently visited places by respondents by household head and spouse

Frequently Visited Places	Household Head	Spouse	Total
Barangay hall	58	42	100
Sayangan	95	57	152
Cooperative	14	9	23
Church	37	28	65
Greenhouse	9	5	14
La Trinidad, Trading Post	17	10	27
Baguio	5	2	7

* Some respondents mentioned multiple places visited
Source: Authors' computations based on primary data

Access and utilization of weather and climate information

Among the types of weather and climate information, tropical cyclone warnings, heavy rainfall warnings, daily forecasts, and ENSO are well-known to households (Table 5). On the other hand, 2–6-month forecasts and climate projections are the least known. Indigenous forecast information is heard by 30 percent of the respondents[3] (Table 5).

[3] See Annexes for more information

Table 5. Respondents who have heard of weather and climate information

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Typhoon	363	0.99	0.12	0	1
Heavy rainfall	363	0.93	0.25	0	1
Daily forecast	363	0.88	0.32	0	1
Biweekly forecast	363	0.29	0.45	0	1
Monthly	363	0.03	0.18	0	1
2–6 month forecast	363	0.01	0.10	0	1
ENSO	363	0.89	0.32	0	1
Press	363	0.46	0.50	0	1
Projections	363	0.06	0.24	0	1
Indigenous	363	0.30	0.46	0	1
Non-PAGASA	290	0.19	0.39	0	1

Source: Authors' computations based on primary data

Tropical cyclone warnings, heavy rainfall forecasts, daily forecasts, and ENSO are also actively sought by the respondents. Except for ENSO forecasts, this information has shorter coverage from the time of issuance to the actual event, which is usually less than 24 hours before the occurrence. It also influences farm activities since typhoons, heavy rainfall, and ENSO can bring devastation and losses. These forecasts are also distributed through various platforms and can receive broad media attention in case of typhoons. Except for ENSO and climate projections, weather and seasonal climate forecasts are the least sought after (Table 6). It can be caused by the long-time frame of forecast coverage, especially for climate change projections. The level of forecast localization also affects interest since this is at the provincial, regional, or national level. In addition to the time frame, the localization level adds complexity and weak end-user interest. Weather forecasts and climate projections are mostly accessible using the PAGASA website and mobile app and do not receive the same level of media coverage for typhoons, heavy rainfall, or ENSO announcements.

Table 7 shows the reported utilization of weather and climate information. Households often use weather warnings and ENSO forecasts, while weather forecasts, climate projections, and indigenous forecasts are the least used. It can be that these weather and climate products are not well-known and therefore have low utilization. Moreover, farmers have difficulty relating the information to their personal farm experiences, considering the time gap from the issuance to the event's occurrence. Finally, a low proportion (16%) of respondent households have ever visited the PAGASA website.

Table 6. Actively sought weather and climate information by respondents

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Respondents actively seek typhoon	363	0.88	0.32	0	1
Respondents actively seek heavy rainfall	363	0.70	0.46	0	1
Respondents actively seek daily forecast	363	0.68	0.47	0	1
Respondents actively seek bi-weekly forecast	363	0.17	0.38	0	1
Respondents actively seek monthly forecast	363	0.02	0.16	0	1
Respondents actively seek 2–6 month forecasts	363	0.01	0.09	0	1
Respondents actively seek ENSO	363	0.64	0.48	0	1
Respondents actively seek press releases	363	0.30	0.46	0	1
Respondents actively seek climate projection	363	0.03	0.17	0	1
Respondents actively seek indigenous forecast	363	0.13	0.33	0	1
Respondents actively seek non-PAGASA information	363	0.13	0.34	0	1

ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' compilation based on primary data

Table 7. Respondents' utilization of weather and climate information by sitio

Weather and Climate Information	Observation	Mean	Standard Deviation	Minimum	Maximum
Typhoon	396	0.80	0.40	0	1
Heavy rainfall	396	0.68	0.47	0	1
Daily forecast	396	0.63	0.48	0	1
Bi-weekly forecast	396	0.20	0.40	0	1
Monthly	396	0.02	0.15	0	1
2-6 month forecast	396	0.01	0.09	0	1
ENSO	396	0.66	0.47	0	1
Press	396	0.29	0.45	0	1
Projections	396	0.04	0.19	0	1
Indigenous	396	0.16	0.36	0	1
Non-PAGASA	396	0.17	0.37	0	1

ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' compilation based on primary data

Table 8 shows respondents' access to various weather and climate information by sitio. Warnings, namely typhoons, heavy rainfall, and daily forecasts are known to the sitios. Monthly, 2-6 months forecasts and climate projections are less heard off. It is also interesting that Tulodan and Macbas have a higher proportion of respondents who have heard of ENSO and press releases.

In terms of access, Macbas has the lowest share of respondents who have access to typhoon, heavy rainfall, and ENSO information. These are also the information Macbas residents actively seek. Tulodan seems to have a higher share of respondents with access to weather and climate information and continues seeking more information. On the other hand, fewer residents from Proper Paoay seek more information on typhoons, heavy rainfall, and daily forecasts.

Table 9 shows utilization and whether the respondents need more weather and climate information explanation. Again, typhoons, heavy rainfall, daily forecast, and ENSO projections are more utilized than other weather and climate information. However, there is a lower share of utilization in Macbas and the highest in Tulodan. Compared with those who heard or have access to those who utilize, the share is lower for utilization. This supports the gap between access and utilization. Seasonal forecasts, except for ENSO and climate projections, are less utilized. Among the three sitios, respondents in Sitio Tulodan need more explanation of weather and climate information they have heard of.

Table 8. Proportion of respondents with access to weather and climate information by sitio and type of information

Weather/Climate Information	Proper Paoay		Tulodan		Macbas	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Heard of	N=176		N=125		N=62	
Typhoon	0.99	0.08	0.98	0.15	0.98	0.13
Heavy rainfall	0.93	0.26	0.93	0.26	0.95	0.22
Daily forecast	0.89	0.32	0.88	0.33	0.89	0.32
Biweekly forecast	0.21	0.41	0.42	0.50	0.23	0.42
Monthly	0.01	0.08	0.09	0.28	0.00	0.00
2-6 month forecast	0.00	0.00	0.03	0.18	0.00	0.00
ENSO	0.82	0.39	0.97	0.18	0.92	0.27
Press	0.39	0.49	0.55	0.50	0.47	0.50
Projections	0.02	0.13	0.15	0.36	0.00	0.00
Indigenous	0.21	0.41	0.50	0.50	0.16	0.37
Non-PAGASA	0.19	0.40	0.19	0.40	0.18	0.39
Access when needed	N=188		N=129		N=79	
Typhoon	0.93	0.25	0.95	0.23	0.78	0.41
Heavy rainfall	0.87	0.34	0.90	0.30	0.75	0.44
Daily forecast	0.83	0.38	0.85	0.36	0.70	0.46
Biweekly forecast	0.20	0.40	0.41	0.49	0.18	0.38
Monthly	0.01	0.07	0.09	0.28	0.00	0.00
2–6 month forecast	0.00	0.00	0.03	0.17	0.00	0.00
ENSO	0.77	0.42	0.95	0.23	0.72	0.45
Press	0.37	0.48	0.54	0.50	0.37	0.49
Projections	0.02	0.13	0.14	0.35	0.00	0.00
Indigenous	0.19	0.39	0.45	0.50	0.13	0.33
Non-PAGASA	0.18	0.39	0.24	0.43	0.14	0.35
Actively seek	N=176		N=125		N=62	
Typhoon	0.84	0.37	0.90	0.31	0.98	0.13
Heavy rainfall	0.64	0.48	0.72	0.45	0.84	0.37

Table 8 *(continued)*

Weather/Climate Information	Proper Paoay		Tulodan		Macbas	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Daily forecast	0.61	0.49	0.78	0.41	0.66	0.48
Biweekly forecast	0.08	0.27	0.34	0.48	0.10	0.30
Monthly	0.01	0.08	0.06	0.25	0.00	0.00
2–6 month forecast	0.00	0.00	0.02	0.15	0.00	0.00
ENSO	0.48	0.50	0.76	0.43	0.85	0.36
Press	0.22	0.41	0.42	0.50	0.27	0.45
Projections	0.01	0.08	0.08	0.27	0.00	0.00
Indigenous	0.08	0.27	0.22	0.41	0.08	0.27
Non-PAGASA	0.07	0.26	0.19	0.40	0.18	0.39

Std. Dev. = standard deviation; N = number of observations; ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' computations based on primary data

Table 9. Proportion of respondents who utilize and need more explanation on weather and climate information by sitio and type of information

Weather/Climate Information	Proper Paoay		Tulodan		Macbas	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Utilized	N=188		N=129		N=79	
Typhoon	0.82	0.39	0.84	0.37	0.70	0.46
Heavy rainfall	0.69	0.47	0.71	0.46	0.63	0.49
Daily forecast	0.64	0.48	0.71	0.45	0.46	0.50
Biweekly forecast	0.12	0.33	0.37	0.49	0.09	0.29
Monthly	0.00	0.00	0.07	0.26	0.00	0.00
2-6 month forecast	0.00	0.00	0.02	0.15	0.00	0.00
ENSO	0.57	0.50	0.84	0.37	0.59	0.49
Press	0.22	0.42	0.44	0.50	0.18	0.38
Projections	0.01	0.07	0.11	0.31	0.00	0.00
Indigenous	0.10	0.30	0.29	0.45	0.09	0.29
Non-PAGASA	0.14	0.35	0.22	0.42	0.14	0.35
Need explanation*						
Typhoon	0.21	0.41	0.34	0.48	0.08	0.28
Heavy rainfall	0.17	0.37	0.32	0.47	0.00	0.00

Table 9 *(continued)*

Weather/Climate Information	Proper Paoay		Tulodan		Macbas	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Daily forecast	0.17	0.38	0.32	0.47	0.00	0.00
Bi-weekly forecast	0.27	0.45	0.49	0.50	0.00	0.00
Monthly	0.00	–	0.45	0.52	–	–
2-6 month forecast	–	–	0.25	0.50	–	–
ENSO	0.19	0.40	0.34	0.48	0.14	0.35
Press	0.14	0.35	0.32	0.47	0.10	0.31
Projections	0.00	0.00	0.37	0.50	–	–
Indigenous	0.08	0.28	0.16	0.37	0.00	0.00
Non-PAGASA	0.12	0.33	0.19	0.39	0.00	0.00

Std. Dev. = standard deviation; N = number of observations; ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
* Various numbers of observations depending on the type of information and sitio
"–" = data not available
Source: Authors' computations based on primary data

In terms of sources of weather and climate information, radio and television are the most common sources of information across the different weather and climate information, except for indigenous forecasts. Indigenous forecasts are usually made by the respondent or taken from other persons and even extension workers. None of the respondents answered PAGASA as a direct source. This implies that information from PAGASA travels to different channels before it reaches the user, or the user is unaware that it came from PAGASA. Moreover, PAGASA also reported while weather segments on the local news use their information on typhoons and heavy rainfall, they often use other sources for day-to-day weather and temperature forecasts. Beyond this, print materials such as broadsheets and tabloids are not identified as weather and climate information sources. Aside from indigenous forecasts, extension workers are not sources of weather and climate information in general.

Meanwhile, the National Disaster Risk Reduction and Management Council is a source of typhoon and heavy rainfall information only but not of other data such as ENSO and climate projections. Relatively short-term information, such as typhoons and heavy rainfall warnings, are well distributed and accessed through various sources than longer-term information, such as climate projection and seasonal climate forecasts, except for El Niño forecasts. This is likely, as typhoons and heavy rainfall have the most tangible and devastating impacts on property and human safety, making it more important to distribute this information effectively.

Regarding how respondents gauge the quality of forecasts, it is not enough that weather and climate information is produced. Other aspects of information should be considered as well. In this study, respondents were asked to rate the weather and climate information based on timeliness, accuracy, and usefulness by asking: "From 1 to 5, how [timely/accurate/useful] do you consider the [information]?" A higher score means a better rating.

Typhoon information gathered the highest ratings for timeliness, accuracy, and usefulness. Heavy rainfall and daily forecasts also received relatively higher ratings. The short-term nature of these types of information (i.e., information is released only hours from the actual event), where forecasting yields more accurate results, might have influenced the rating.

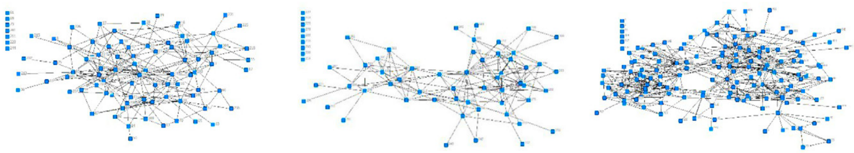
Typhoons, heavy rainfall, and daily forecasts have the highest ratings for their timeliness, but at best, at only 3.6/5. ENSO forecast is rated moderately. The general rating for accuracy among weather and climate information is moderate. This reflects views in Atok that PAGASA forecasts are different from their experiences on the field, and thus localized forecasts are needed. Usefulness ratings are generally higher compared to timeliness and accuracy ratings. Again, typhoons, daily forecasts, and heavy rainfall have higher ratings, while indigenous forecasts are rated relatively low.

Social networks: Interhousehold

Figure 6 shows the kinship, friendship, and economic ties in the three areas: (a) Tulodan, (b) Macbas, and (c) Proper Paoay. In the graphs, a node pertains to a household in the sitio. A link (denoted by a line) is drawn between two pairs of nodes if at least one direct social or economic connection exists between them. It must be noted that the lines are undirected (without arrows) to denote reciprocal relations.

The three study areas exhibit varying network cohesion parameters (Table 10). Based on the specified social ties, Sitio Macbas is the most cohesive, while Proper Paoay is the least cohesive. In Macbas, the whole network has a density of 0.086, meaning 8.6 percent of all possible links are actual ties. This is relatively lower in Tulodan (6.1%) and Proper Paoay (4.4%). Macbas also has the lowest average geodesic distance of 2.8, which means that it is relatively easier to reach other nodes (as it would take fewer steps, on average) than those in Proper Paoay (3.3) and Tulodan (2.8). In terms of degree, or the number of direct links, households in Proper Paoay have relatively greater connectivity at 6.8 links per household than those in Macbas (5.3) and Tulodan (5.4).

Figure 6. Network of interhousehold social relations among respondents by sitio



Tulodan Macbas Proper Paoay

Source: Authors' illustration based on primary data

To understand how these network parameters would compare to another setting in the Philippines, Tabuga (2018) showed the network density of a lowland rural fishing village is 0.067 (6.7%) with an average geodesic distance of 2.9. The rural village of interest in that study, though considered rural, is situated near the national road, making it far more accessible than the Atok sites.

It is important to present the above findings alongside the other characteristics of the areas. Proper Paoay is considered the least rural among the three sitios as it is nearest to the municipality center. Households in Proper Paoay are more plentiful, and their dwellings are close to each other. Sitio Tulodan, as a community, occupies a wider map area and thus seems more dispersed. However, a closer inspection shows tight clusters of households.

Table 10. Whole network attributes of respondents by sitio

Parameter	Proper Paoay	Tulodan	Macbas
Density	0.044	0.061	0.086
Average degree	6.800	5.400	5.302
Diameter	7.000	6.000	6.000
Average geodesic distance	3.322	2.858	2.779
Number of nodes	155	90	63
Number of ties	1,054	486	334

Source: Authors' computations based on primary data

It is these clusters of households that are, in turn, located relatively far from one another. On the other hand, the households in Sitio Macbas, as a whole, live closer together within a smaller map area but exhibit no clusters of households like in Tulodan. Sitio Macbas also lacks a dense hub of activities like Proper Paoay does. Sitio Macbas and Tulodan are also more remote than Proper Paoay.

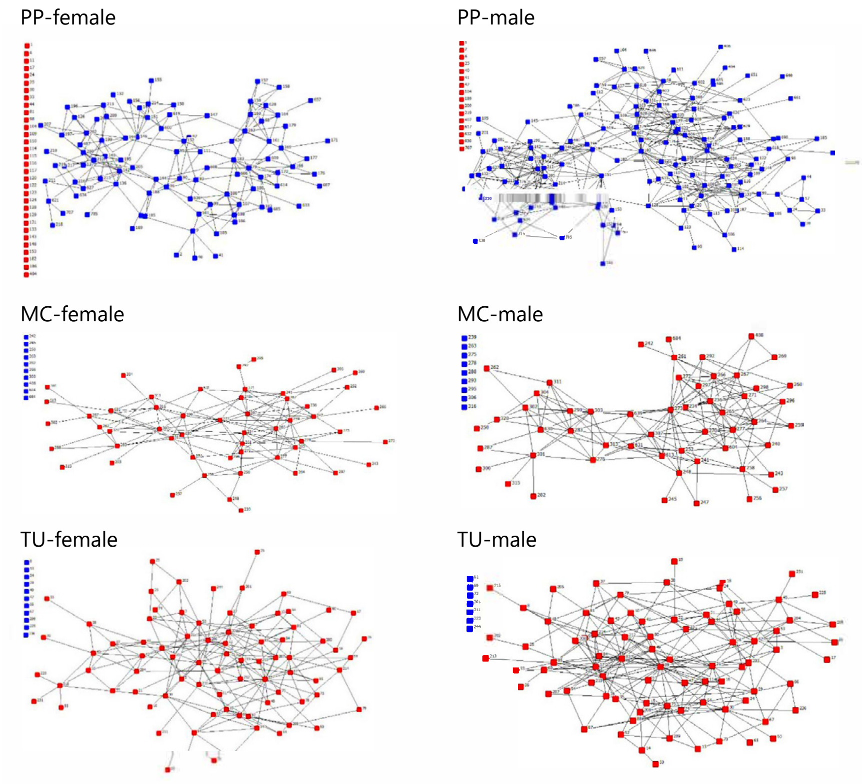
The demographics of each sitio are also varied. While sitio-level data on the socioeconomic standing of the communities is scarce, there is information from the Community-Based Monitoring System (CBMS) that disaggregates data down to the barangay level. Per the 2014-2017 CBMS, Barangay Paoay, where sitio Proper Paoay is located, experiences lower poverty levels (8.3%) than Barangay Cattubo (32.8%), where sitios Macbas and Tulodan are located. Other indicators that Barangay Paoay is better off than Barangay Cattubo include greater access to safe water supply (~35% against Cattubo's 7%) and sanitary toilets (96% against 81%). Both barangays have similar rates of children aged 6-15 who are not in school (nearly 1%), while Barangay Paoay has a lower unemployment rate (0.2% against 1.9%).

Given these characterizations of the number and spread of household dwellings in the study areas, it is expected that households living close to each other in a relatively small geographic area, such as Macbas, would be more socially cohesive. Being remote also suggests it attracts few in-migrants, creating a relatively tightly knit community. The difference in the network cohesion between Macbas and another remote area (Tulodan) can be attributed to the clustering of household dwellings and to being scattered in a wider physical space in the latter. On the other hand, Proper Paoay, which has relatively greater economic activities than the other two sitios, is most likely to attract people from other areas, making social relations, as a whole, less cohesive because of their inclusion. This is also possibly due to its better accessibility than other sitios.

Social networks of men and women

While the preceding graphs show the networks among households regardless of the point of reference (i.e., whether head or spouse), Figure 7 shows the household networks identified by the sex of the point of reference. These graphs help understand any variation in the networks of men and women. A visual appreciation shows that the network identified by men appears to differ from that by women in each sitio. The network parameters calculated from these graphs consistently show that household networks of male respondents are relatively more cohesive, as demonstrated by higher density, higher average degree, and shorter average distance (Table 11). The calculations are based uniformly on the total number of households. If those for the female respondents were normalized based only on the total number of households or nodes with female respondents, then the parameters become relatively on par with those of male respondents. In any case, these results suggest complementarity in men's and women's networks.

Figure 7. Social networks of respondents by sitio and sex (node color by component)



PP = Proper Paoay; MC = Macbas; TU = Tulodan
Note: Graphs may include alters outside the sitio
Source: Authors' illustration based on primary data

Table 11. Social cohesion measures among respondents by sex and sitio

Parameter	Social Links			Peer Advice and Resource Network	
	Female	Female*	Male	Female	Male
Proper Paoay					
Number of nodes	155	105	155	155	155
Number of ties	434	378	806	336	806
Average degree	2.800	3.600	5.200	2.168	5.200
Density	0.018	0.035	0.034	0.014	0.034
Components	60	22	17	62	14
Connectedness	0.382	0.638	0.804	0.366	0.839
Fragmentation	0.618	0.362	0.196	0.634	0.161
Closure	0.251	0.242	0.264	0.198	0.274
Average distance	3.855	3.658	3.624	4.328	3.606
Diameter	9	9	9	10	7
Macbas					
Number of nodes	63	54	63	63	63
Number of ties	250	210	334	186	294
Average degree	3.968	3.889	5.302	2.952	4.667
Density	0.064	0.073	0.086	0.048	0.075
Components	11	10	10	19	10
Connectedness	0.706	0.662	0.733	0.507	0.733
Fragmentation	0.294	0.338	0.267	0.493	0.267

Table 11 *(continued)*

Parameter	Social Links			Peer Advice and Resource Network	
	Female	Female*	Male	Female	Male
Closure	0.262	0.261	0.350	0.295	0.333
Average Distance	2.902	2.753	2.779	3.075	2.904
Diameter	7	6	6	8	6
Tulodan					
Number of nodes	90	81	90	90	90
Number of ties	396	390	486	256	410
Average degree	4.400	4.815	5.400	2.844	4.556
Density	0.049	0.060	0.061	0.032	0.051
Components	12	6	8	20	11
Connectedness	0.769	0.880	0.850	0.620	0.789
Fragmentation	0.231	0.120	0.150	0.380	0.211
Closure	0.198	0.200	0.243	0.194	0.216
Average distance	3.105	3.028	2.858	3.740	3.067
Diameter	7	7	6	8	7

* Normalized based on the number of households with female respondents only
Source: Authors’ computations based on primary data

Weather and climate information networks among households

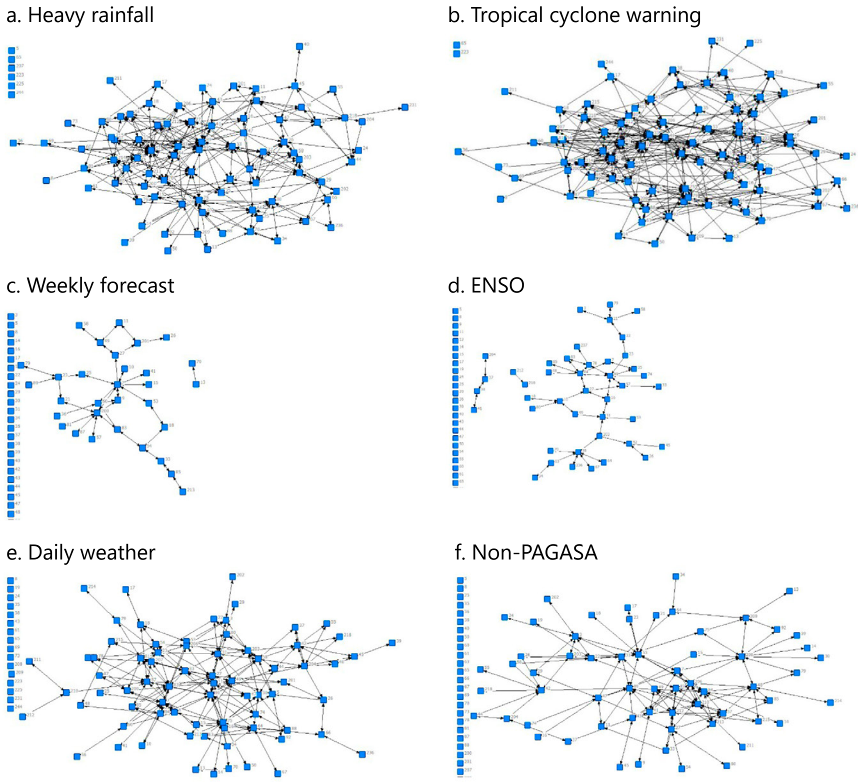
One of the study's objectives is to examine weather and climate information by type—whether networks vary by type of information. The information networks are compared visually and objectively by looking at network cohesion parameters. Are some networks more cohesive than others? Do networks share the same central nodes? The graphs are shown as directed graphs (with arrows) where a line connecting any pair of nodes (representing the households in the sitio) denotes the flow of information. The direction of the arrow illustrates the direction of the information flow. An arrow emanating from a node shows that the node shares information with the one at the receiving end of the arrow. If an arrow is going out and coming in, it means the node is both a recipient and a disseminator of information. Regardless of the extent of connections, we call each graph a "network".

Weather and Climate Information (WCI) network: Tulodan

Figure 8 shows Tulodan's internal (within-sitio) information networks of different weather and climate information. Only six types of WCI networks (i.e., tropical cyclone warning, heavy rainfall warning, daily weather forecast, weekly forecast, ENSO, and non-PAGASA information) were drawn. There is very minimal sharing of information regarding monthly and 2–6-month forecasts, as well as narratives, climate projections, and indigenous weather and climate information. Hence no graphs were created for these.

Among the types of weather and climate information, those with a relatively greater extent of being shared across households are heavy rainfall and tropical cyclone warnings, as shown by the smaller number of isolated nodes (i.e., nodes that are not connected to the rest, as shown in left side) in these graphs (see items a and b, Figure 8). The number of households sharing tropical cyclone warnings is the highest (88), followed by heavy rainfall warnings (84). There are also relatively more households included in the information network of daily weather forecasts (74) compared to the networks involving ENSO, weekly projections, and non-PAGASA forecasts. These three networks (i.e., tropical cyclone, heavy rainfall warning, and daily weather forecast) are also characterized by a large network component or a cluster of households connected to each other. Interestingly, the non-PAGASA network shares this same character as it comprises one big component and many isolated households. In contrast, the rest of the network graphs—weekly forecasts and ENSO—are relatively sparser and made up of several ‘star’ graphs connected to each other, where large numbers of nodes are isolated from the main component (i.e., the main cluster). A pure ‘star’ graph is one where one node (central node) is connected to several nodes that are not connected to each other but only through the central node. Such a centralized system presents some limitations as the central node controls the flow of information. In the weekly forecast and ENSO graphs, these star subgraphs are connected to each other by one of the surrounding spokes of the star.

Figure 8. Weather and climate information networks of respondents by type, Sitio Tulodan



ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors’ illustration based on primary data

An analysis using more objective measures of cohesion calculated using the UCINET software package shows that information networks involving tropical cyclones and heavy rainfall warnings are more cohesive than other networks. The density of the tropical cyclone network is 0.089 or 8.9 percent, while that for heavy rainfall warning is 0.057 or 5.7 percent (see Table 12). Both densities are higher compared with other networks. These two also have a lower number of components or groups. It must be noted that an isolated node is considered a component. Hence, the more isolated nodes there are, the greater the number of components and the more fragmented the network is. The measured fragmentation score illustrates this because the two networks have the lowest score. The average degree in the tropical cyclone network is the highest at nearly 8, showing that a typical node is directly connected to 8 other nodes. The average degree in heavy rainfall warning networks is 5, while others have lower average degrees. Another measure of cohesion that shows the two networks being more cohesive is the average geodesic distance or the average number of steps a node can reach other nodes. The tropical cyclone network has an average distance of 2.5, while the rainfall warning network has 2.9. It takes relatively fewer steps for one node to reach the rest of the nodes in the tropical cyclone network than in the other WCI networks.

The two most cohesive WCI networks in Tulodan share many core nodes or households. Most core households in the heavy rainfall warning network are shared with the tropical cyclone warning network. In the latter, 15 of 19 (i.e., nearly 80%) core households can also be found in the former. Note that the core nodes act as a glue that binds the network together. It is important to note that the tropical cyclone network, the most cohesive among the WCI networks, approximates the network parameters of Tulodan's social and economic networks. The two networks have a similar average geodesic distance of 2.5 and comparable network densities. There are 770 ties in the social network and 709 in the tropical cyclone network. Furthermore, 17 of 19 core nodes in the tropical cyclone network (i.e., 17 of 27 core nodes of the social network) are shared with the sitio's social network. This suggests that the tropical cyclone network is a subset of the sitio's social network, as roughly the same actors bind the networks together.

Table 12. Measures of whole network cohesion among respondents by type of weather and climate information, Sitio Tulodan (number of nodes=90)

Measure	Tropical Cyclone	Heavy Rainfall	Daily Weather	Weekly Forecast	ENSO	Non-PAGASA
Number of ties	709	459	330	61	78	225
Average Degree	7.878	5.100	3.667	0.678	0.867	2.500
Density	0.089	0.057	0.041	0.008	0.010	0.028
Components	3	11	18	66	62	33
Fragmentation	0.044	0.171	0.335	0.926	0.933	0.565
Closure	0.270	0.195	0.219	0.047	0.077	0.162
Average Distance	2.526	2.927	3.144	3.411	3.448	3.176
Diameter	5	7	7	9	8	8

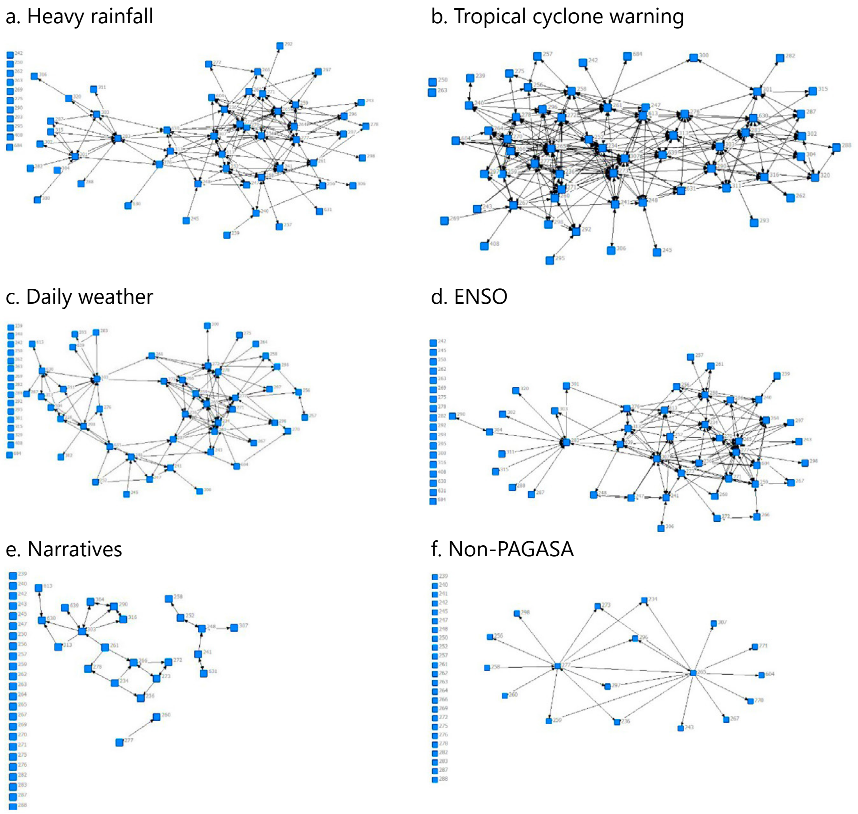
ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' computations based on primary data

WCI network: Macbas

Figure 9 shows the information networks of the different WCI in Macbas. Only six graphs were drawn, and these are for heavy rainfall warnings, tropical cyclone warnings, daily weather forecasts, ENSO, narratives, and non-PAGASA weather and climate information. There is very limited sharing of weekly, monthly, and 2–6-month forecasts, climate projections, and indigenous knowledge. Thus, no network graph is drawn for each of these WCI. For those with network graphs, a visual appreciation reveals stark differences across types of WCI.

As in the case of Tulodan, the graphs show that the tropical cyclone network is the most cohesive among all types of networks. There is more sharing of this type than others based on its smallest number of isolated nodes. The information networks involving narratives (panel e) and non-PAGASA (panel f) information are shown to be more fragmented—that is, many of the households in the sitio are not linked to the connected component of the sitio network. The panels a, c, and d, corresponding to heavy rainfall, daily weather, and ENSO, are more cohesive than the other two networks (i.e., narratives and non-PAGASA) because of the presence of a single large component despite some isolated nodes. Except for the tropical cyclone network, few nodes seem to act as bridges between major clusters that would otherwise be disconnected in WCI networks.

Figure 9. Weather and climate information networks by type, Sitio Macbas



ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' illustration based on primary data

Table 13 objectively illustrates how the tropical cyclone warning network is more cohesive than the others. In this network, the average node has a degree or direct connections of around 7.5, the highest among all the graphs. Its density of 12.1 percent is also the highest. This is because it has a higher number of ties (i.e., 471) than the rest of the WCI networks. The networks of heavy rainfall and ENSO have densities of 6.9 and 6.1 percent, respectively. The rest have very low densities compared to these three networks.

In terms of components or groups, the tropical cyclone network has fewer network components than the rest. Each node in this network is, on average, at a geodesic distance of 2.5 from all other nodes/households.

Table 13. Measures of whole network cohesion by type of weather and climate information, Sitio Macbas (number of nodes=63)

Measure	Heavy Rainfall	Tropical Cyclone	Daily Weather	ENSO	Narratives	Non-PAGASA
Number of ties	268	471	178	238	40	28
Average degree	4.254	7.476	2.825	3.778	0.635	0.444
Density	0.069	0.121	0.046	0.061	0.010	0.007
Components	14	3	25	20	52	57
Fragmentation	0.347	0.063	0.537	0.515	0.978	0.970
Closure	0.323	0.364	0.261	0.317	0.333	0.131
Average distance	2.749	2.472	2.970	2.512	1.678	2.286
Diameter	6	5	7	6	4	4

ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' computations based on primary data

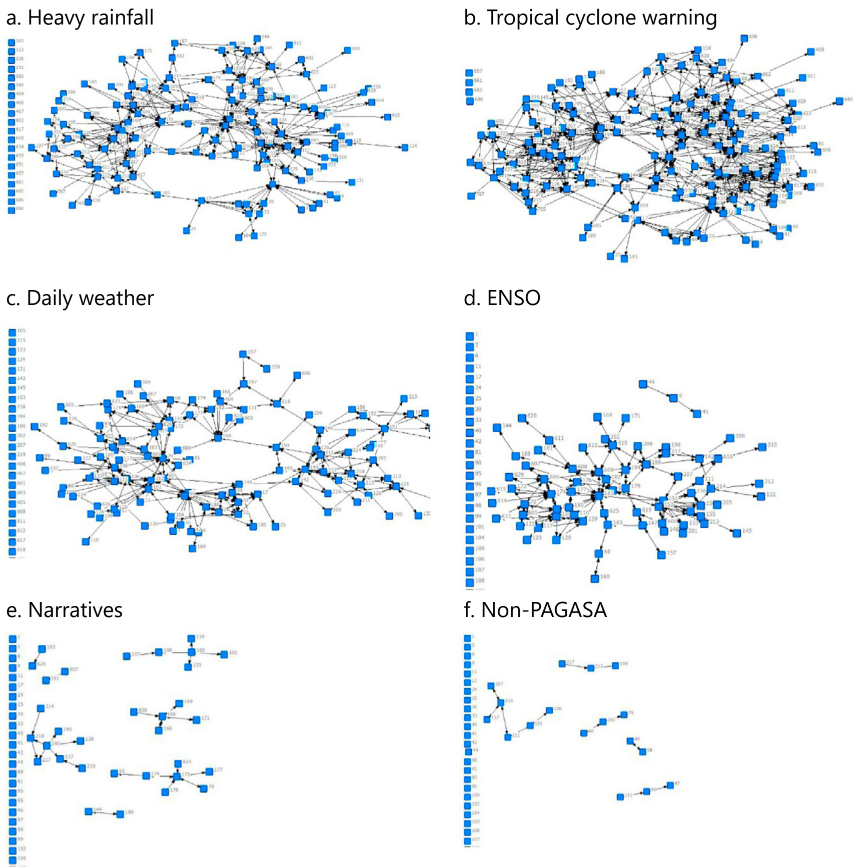
The average geodesic distance is slightly lower than in heavy rainfall, daily weather, and ENSO networks. This further illustrates that actors in these other networks (i.e., heavy rainfall, daily weather, and ENSO) take relatively longer paths to reach all other network members, hence the longer average distance. It should be noted that although the networks for narratives and non-PAGASA have lower average distances, the connected networks are way smaller. It takes fewer steps to reach others because there are not many other network members, as most nodes are not part of the connected network; they are isolates. The closure score merely reflects the same idea that the average distance shows; it is highest in the tropical cyclone network because of the relative ease in a node's ability to reach other nodes. Therefore, it is important to note that the tropical cyclone network is on par with the kinship and friendship network in terms of network cohesion.

There are also significant similarities among networks of WCI as far as central nodes are concerned. Most central nodes in tropical cyclone networks are similar to those in heavy rainfall warning networks. This is also true with the daily weather forecast and tropical cyclone networks. Albeit the differences in the whole network attributes, it is important to note such similarities.

WCI network: Proper Paoay

The WCI networks by type shown in Figure 10 mimic the pattern in the other sitios. Among the information networks, those of the heavy rainfall and the tropical cyclone warnings are more extensive and cohesive than the other types. The tropical cyclone network, in particular, includes the most number of households as there are only four isolated households; the overwhelming majority are connected in one big network component. This is also the case for the heavy rainfall warning network, although it has more isolated nodes than the tropical cyclone network.

Figure 10. Weather and climate information networks by type, Sitio Proper Paoay (number of nodes=155)



ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' illustration based on primary data

The daily weather forecast and ENSO networks also show significant sharing among several households, as shown by a large component. In contrast, there is very little information sharing with respect to narratives and non-PAGASA information. The other types of WCI (i.e., weekly, monthly, 2–6-month climate projections and indigenous forecasts) are not included because of very minimal to no information sharing among households.

The calculated network parameters provide more details about the comparison. The number of ties involved in the tropical cyclone warning network, at 1,071, is the highest, followed by that in heavy rainfall (616), daily weather forecast (403), ENSO (268), narratives (33) and non-PAGASA (21). The tropical cyclone network has the highest average degree, density, and closure but has the lowest fragmentation score and the number of components or groups (see Table 14). Apart from narratives and non-PAGASA networks, the tropical cyclone network has the lowest average distance, indicating the ease of reaching other nodes. The low average distance in the narratives and non-PAGASA networks is typical of small-group networks. Within a component, it is relatively easier to reach others because there are fewer members.

In terms of similarities in the composition of the central nodes, the majority (58%) in the tropical cyclone network is shared with that in the heavy rainfall network. In contrast, 62 percent of ENSO central households are shared with the tropical cyclone network.

Table 14. Measures of whole network cohesion by type of weather and climate information, Sitio Proper Paoay (number of nodes=155)

Measure	Heavy Rainfall	Tropical Cyclone	Daily Weather	ENSO	Narratives	Non-PAGASA
Number of ties	616	1071	403	268	33	21
Average degree	3.974	6.910	2.6	1.729	0.213	0.135
Density	0.026	0.045	0.017	0.011	0.001	0.001
Components	25	7	48	89	148	146
Fragmentation	0.265	0.064	0.479	0.803	0.998	0.998
Closure	0.259	0.288	0.230	0.259	0.043	0
Average distance	3.725	3.223	4.111	3.312	1.483	1.632
Diameter	8	7	9	7	3	4

ENSO = El Niño Southern Oscillation; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration
Source: Authors' computations based on primary data

Network sources of WCI

Do people get WCI from closer, more trustworthy relations than weaker ties or random sources? This study looked into the nature of links among respondents who shared any of the top 3 types of weather and climate information with one another (Table 15). Specifically, it provides the proportion of the information exchanges by relation categories. Note that if two individuals (from different households) shared information, these were counted as two exchanges. The data did not include intrahousehold exchanges. The categories included are not mutually exclusive; neighbors can also be members of peer advice networks. The categorization aims to have a more nuanced look at the nature and characteristics of relations involved in WCI sharing.

Table 15. Sources of any weather and climate information (heavy rainfall, tropical cyclone warning, daily weather forecast) by nature of relations

Type of relation	Sources			Total Links (Individual Level)		
	Proper Paoay	Macbas	Tulodan	Proper Paoay	Macbas	Tulodan
	(1)	(2)	(3)	(4)	(5)	(6)
Kin	43.4	68.8	64.7	44.2	69.5	64.5
Close friends	13.4	6.6	14.8	13.7	7.1	15.0
Neighbor	45.8	57.4	41.1	44.5	54.8	41.7
Other friends	10.9	11.4	12.5	10.9	10.7	12.1
Economic network	13.8	0.6	2.3	13.7	0.6	2.4
Peer farm advice network	82.6	66.1	74.7	80.0	64.4	72.9
Peer resource network	39.2	44.4	42.4	37.3	42.9	41.5
Peer health advice network	72.8	91.0	80.5	69.9	89.8	79.2
Total exchanges/ information ties	806.0	333.0	601.0	857.0	354.0	619.0

Source: Authors' computations based on primary data

In Proper Paoay, 806 information exchanges happened between individual respondents. Most (83%) of the exchanges occurred among peer farm advice network members. Farm advice is any form of advice being exchanged about farm activities. Many people (73%) sharing WCI are also linked to one another via other peer advice networks (i.e., health). Regarding social ties, the more common sources of WCI are neighbors (46% of the exchanges). Less than half (43%) of the exchanges involved kinship relations. A nonnegligible proportion (40%) of the exchanges also happens among peer resource network members (i.e., farmers/farm workers sharing farm inputs and other resources).

Tulodan's and Macbas' cases have quite similar patterns—that is, the types of links that prevailed in these communities are peer advice networks (health and farming), which is also the case of Proper Paoay. Their difference from Proper Paoay is that kinship sources are more common among individuals in the two smaller sitios than neighbors, friends, and economic networks. In all the communities, economic or work-related networks are the least common links among those who share information about the top three types.

It must be noted that these figures approximate those in the total links, which means that some types are more prevalent than others in terms of sources of WCI because these are the more common types of ties that exist in the communities in general. Nonetheless, there are relatively higher proportions for peer advice and resource networks (for all the sitios) and neighbors (for Proper Paoay and Macbas) than in the total links. It appears that WCI is just among the things these network members share. Thus, sharing of WCI happens among people who trust each other and are physically proximate to one another (such as neighbors). This is understandable because of WCI's characteristics; it is useful only for a certain period. One is likely to get from common conversations and routine interactions with people inside social circles.

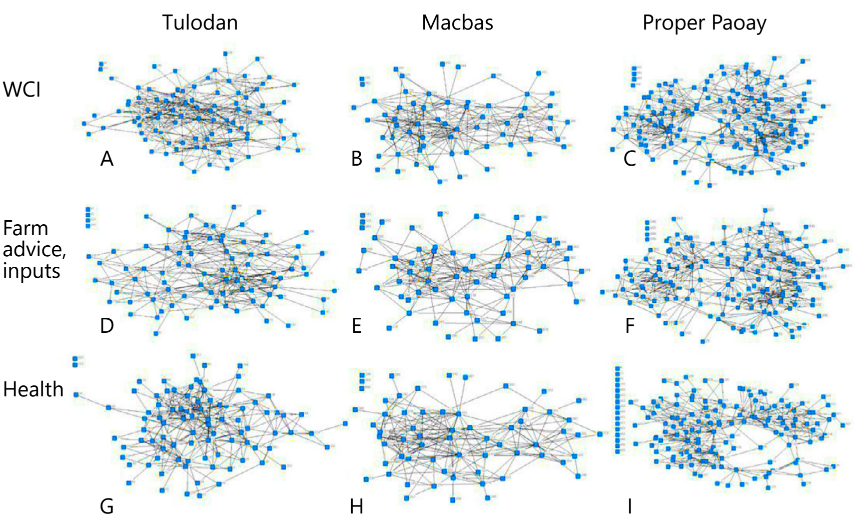
WCI network comparison with other networks

This study also examines whether WCI networks are similar in characteristics to other types of networks in the communities. This helps better understand the networking dynamics in the areas of interest. For instance, if WCI networks are found to be similar to other networks, then efforts to improve access and utilization of WCI can be applied to any other network to yield the desired outcomes. Such improvisation is valuable in contexts of high resource constraints.

Figure 11 shows the merged WCI network, farm advice and inputs network, and health information network. The combined WCI network is formed by consolidating any WCI sharing. The farm advice and input networks show the links among households in sharing farm-related advice and farm inputs. In contrast, the health information network reflects the sharing of health information among households.

A visual appreciation of Figure 11 shows their striking similarities in that almost all households are integrated into the main component. The number of ties is highest in the WCI for all sitios, which suggests greater interaction than health information, farm inputs, and advice (see Table 16). WCI network, likewise, has the highest average degree and density. It has the lowest average distance, although the difference is very minimal. Therefore, the WCI network is the most cohesive among the three.

Figure 11. Whole networks by type of network and by sitio



WCI = weather and climate information
Source: Authors' illustration based on primary data

In terms of the central nodes that bind the networks together, the similarities are likewise evident. For instance, in Tulodan, 17 nodes were determined by the UCINET software as the core nodes in the

WCI network. Of this number, 14 (82%) are shared with the farm advice and inputs network, while 15 (88%) are shared with the health network. The correlation of various parameters across network types was obtained to supplement the comparison (Table 17). In Tulodan, being a core (or central) household returns a correlation coefficient ranging from 0.55 to 0.63. This means that being core in one type of network correlates to being one in the other. The correlation coefficient among centrality measures degree, betweenness, and eigenvector ranges from 0.71 to 0.88.

In Macbas, farm and health networks, being at the core of WCI, are highly associated with a correlation coefficient ranging from 0.6495 to 0.7611. In Proper Paoay, the correlation coefficient of being core among the three networks ranges from 0.4280 to 0.6397. This is relatively lower than in Tulodan and Macbas, meaning these networks have some variety. The other measures, though, have high correlation coefficients. Overall, these three networks have huge similarities to the actors that bind households together.

Table 16. Measures of whole network cohesion by type of weather and climate information

Measure	WCI	Farm Advice, Inputs	Health
Sitio Tulodan (number of nodes=90)			
Number of ties	754	596	616
Average degree	8.378	6.622	6.844
Density	0.094	0.074	0.077
Components	3	5	3
Fragmentation	0.044	0.087	0.044
Closure	0.281	0.249	0.271
Average distance	2.470	2.684	2.746
Diameter	5	5	7
Sitio Macbas (number of nodes=63)			
Number of ties	476	408	448
Average degree	7.556	6.476	7.111
Density	0.122	0.104	0.115
Components	3	4	4
Fragmentation	0.063	0.094	0.094
Closure	0.367	0.319	0.345

Table 16 *(continued)*

Measure	WCI	Farm Advice, Inputs	Health
Average distance	2.464	2.606	2.468
Diameter	5	6	5
Sitio Proper Paoay (number of nodes=155)			
Number of ties	1,128	1,020	860
Average degree	7.277	6.581	5.548
Density	0.047	0.043	0.036
Components	5	5	17
Fragmentation	0.051	0.051	0.196
Closure	0.298	0.287	0.302
Average distance	3.155	3.288	3.461
Diameter	7	7	9

WCI = weather and climate information
Source: Authors' computations based on primary data

Table 17. Correlation coefficient among weather and climate information, farm advice and inputs, and health information networks by sitio

Score	Tulodan	Macbas	Proper Paoay
Being Core	0.5513-0.6319	0.6495-0.7611	0.4280-0.6397
Degree	0.8450-0.9328	0.9287-0.9728	0.8862-0.9695
Betweenness	0.7243-0.8842	0.8854-0.9740	0.8999-0.9802
Eigenvector centrality	0.7410-0.9068	0.8670-0.9643	0.8242-0.9612

Source: Authors' computations based on primary data

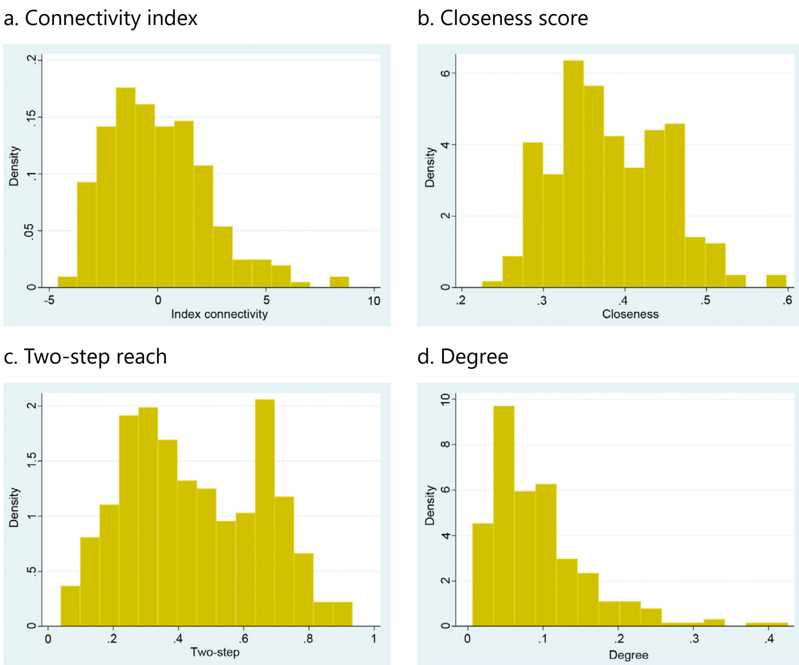
Therefore, these findings suggest that tapping peer advice networks, resource networks, or even health information networks for improving households' access and utilization of weather and climate information is a practical approach that will likely yield an effective outcome.

Characteristics of central nodes

Understanding the characteristics of central actors is most useful for identifying potential information disseminators and injection points should there be a need for social influencing, like in the use of scientific information and perhaps new technology in agriculture. To determine the correlates of centrality, simple OLS regression models were estimated.

The dependent variables are various network parameters calculated through the UCINET based on the social ties of the households. We selected only the parameters with a near-normal distribution or exhibiting a bell-shaped distribution: degree, closeness, and 2-step reach centrality. An index for connectivity was also developed via Principal Components Analysis out of several network parameters. The histograms of these variables are shown in Figure 12.

Figure 12. OLS regression of dependent variables



OLS = Ordinary least squares
Source: Authors' illustration based on primary data

Meanwhile, the explanatory variables comprise demographic (e.g., age and years of education of the head, number of household members) and economic variables—asset indices (calculated through principal components analysis (PCA) involving basic phone, smartphone, tractor, water pump), house and vehicle ownership. Farming characteristics such as the area of farmland operated, years spent in farming by the head, and exposure to outside financial resources proxied by availing credit were also included.

A variable that controls for geographic constraints that can potentially impede a person's ability to interact with many people was also included in the models. Geographic constraint pertains to the distance (in meters) from the respondent's dwelling to the place frequently visited by the respondent, for instance, a market or church. The summary statistics of the different variables are shown in Table 18.

Table 18. Summary statistics in regression estimations, household level

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Dependent variables					
Degree	228	0.0944	0.0677	0.0060	0.4260
Two-step reach	228	0.4463	0.2066	0.0390	0.9330
Closeness	228	0.3832	0.0683	0.2250	0.5980
Connectivity index	228	0.0056	2.3433	-4.6120	8.8380
Individual characteristics					
Age of head	229	43.2149	14.5114	19.0230	84.0190
Age of head, squared	229	2077.1830	1370.6300	361.8590	7059.2200
Years of education of head	225	8.2756	3.4582	0.0000	16.0000
Being *Kankanaey*	228	0.6842	0.4659	0.0000	1.0000
Years in farming by head	228	17.1974	13.4302	0.0000	57.0000
Household characteristics					
Number of household members	229	3.9039	2.4079	1.0000	20.0000
Vehicles owned	229	0.4672	0.8455	0.0000	5.0000
House ownership	228	0.7193	0.4503	0.0000	1.0000
Size of farm operated	229	37.1481	132.1140	0.0000	800.0000
Ever availed credit	229	0.4847	0.5008	0.0000	1.0000
Asset index	228	0.0022	1.3106	-1.6130	4.4970
Distance to place frequented (km)	229	3.9690	13.8830	0.0000	120.0000

km = kilometer
Source: Authors' computations based on primary data

The regression results (Table 19) show that few explanatory variables significantly correlate with node centrality when other factors are held constant. None of the individual characteristics, such as educational attainment or ethnicity, matter. The most consistent outcome is that more central households possess more vehicles. Possession of vehicles in the upland, rural setting with significant geographic constraints is expected to correlate with sociability, as these are crucial in farm production and the movement of people. People who ferry products and people from the area to other places are relatively more popular. House ownership seems to be associated with having more direct links (degree) but does not significantly correlate with other centrality parameters. Interestingly, the more well-off households, as shown by the asset index, are less likely to have high node centrality based on this sample of upland communities. Perhaps because their need for social support from others is much lower than less endowed people. This is important evidence; it does not support programs that select relatively wealthy people as reference points, assuming they are more popular and capable of reaching more people.

As expected, being far from venues where people can interact with one another is negatively correlated with centrality. The most central households are those situated near areas of congregations. Those in the periphery of the social network also live in the periphery, in physical terms. There is another interpretation of this result. Since the place people frequently visit differs across households, those who often go to farther places are relatively less central than those who just move within the sitios. Those who travel to the city center and even to more distant trading posts have fewer chances to interact with the local population and are therefore less known by others in the sitio.

Centrally positioned households do not seem to exhibit different behavior from the rest in terms of the main source(s) of WCI. For heavy rainfall warnings and daily weather forecasts, radio and TV are the most common sources, regardless of the relative position in the network. There is a deviation in the sources for typhoon warnings. Most (81%) of the time, central households obtained tropical cyclone warnings from TV; in 23 percent of the cases, the sources are other persons. The rest of the households have more varied sources: radio and TV being the main sources, although a quarter reported that they get it from other people.

Table 19. Regression results by parameter, all sitios

Variable	Degree		2-Step Reach		Closeness		Connectivity Index	
Individual characteristics								
Age of head	0.00454	*	0.01498	*	0.0041767	*	0.16063	*
Age of head, squared	-0.00004		-0.00013	*	-3.401E-05		-0.00130	
Years of education of head	-0.00137		0.00254		0.0003599		0.01060	
Being Kankanaey	0.01012		0.05166		0.0198346		0.25735	
Years in farming by head	-0.00060		-0.00178		-0.0006971		-0.01904	
Household characteristics								
Number of household members	0.00324		0.01022		0.003569		0.08983	
Vehicles owned	0.01749	**	0.05876	***	0.0202766	***	0.67442	***
House ownership	0.02714	*	0.05256		0.0230483		0.41831	
Size of farm operated	0.00003		0.00009		2.904E-05		0.00137	
Ever availed credit	0.00008		0.03922		0.0110176		0.01740	
Asset index	-0.01069	**	-0.05047	***	-0.0155509	***	-0.40609	**
Distance to place frequented (km)	-0.00064	*	-0.00224	*	-0.0007685	**	-0.02422	*
Constant	-0.04473		-0.08148		0.2256361	***	-5.10120	**
R2	0.23000		0.27580		0.2904000		0.20840	
N	224		224		224		224	

R2 = R-squared; N = number of observations
* p<.05; ** p<.01; *** p<.001
Source: Authors’ computations based on primary data

Based on the regression analysis, the profile of central households or actors in upland communities is summarized as follows:

1. *People who live near venues of social gatherings* (e.g., the Barangay Hall of Cattubo and church for people in Macbas and Tulodan; Cooperative Store for Macbas; Sayangan market for those in Proper Paoay). Proximity to these areas enables people to interact more with others within an extremely challenging physical environment where there are limited means of communication due to poor technological infrastructure.
2. *Those with greater means of transport essential for people to navigate the area.* Even people living in far areas but with means of transport are good candidates for information hubs because their mobility enables them to interact more with other people;
3. *Those with the largest dwellings,* particularly in areas near the business center like Proper Paoay
4. *People who come from the largest clans* because they are more likely to extend their reach to their relatives; also, original settlers in the areas who probably know other long-term members of the community
5. *Those who are members of agricultural cooperatives and farmer's organization*s in most remote areas like Brgy. Cattubo. Members of farmer's organizations in places like Proper Paoay may also be selected if they satisfy the other criteria.

Correlates of access and utilization of weather and climate information

This study adopted a more active definition of access and utilization— actively searching for all the major types of weather and climate information (e.g., tropical cyclone warning, heavy rainfall warning, daily weather forecast, ENSO) and utilizing them in farming decisions. The dependent variable is, therefore, a dummy variable for being both an active seeker of all four major WCI and a utilizer of all these types in farm decisions. The unit of analysis is the individual because information for both the head and spouse (if any) is available. This study also looks at the relationship between the dependent variable and connectedness or network centrality. Their relationship is expected to be positive—that is, the more central a person is, the more likely he/she utilizes weather and climate information.

The individual-person explanatory variables are age, age squared, estimated years of education, and years in farming. All these variables are meant to control the skills level and experiences of the individual. The expected associations are positive. Meanwhile, the household characteristics included are the number of household members, a dummy variable for having availed credit ever, the number of smartphones owned, an asset index that was created through PCA from various durable assets, the number of vehicles the households own, distance to place frequented, log of the size of the farm the household operated. The number of household members and asset index are standard demographic and economic factors. Access and utilization of weather by people from different segments may also vary. The number of smartphones owned controls for the ability of the household to access information through the PAGASA website, other internet sources, or some weather-based applications. The dummy variable for having availed of credit ever controls for the need for sources of financing outside the household. This is likely associated with a greater likelihood of searching for and utilizing weather and climate information because of the greater need to improve productivity; the household may not have adequate resources to compensate for losses. The number of vehicles owned was included because it is possibly linked with greater farm productivity, which may motivate people to be more proactive. The variable controlling for physical distance to the person's appointed place of congregation was also included to proxy people's reach, possibly positively correlated with access and utilization. The log of the size of the farm operated is for controlling the risks faced by the household; the bigger the area, the greater the risks to their livelihood, hence, the need to be more proactive with farming decisions.

The centrality parameters of interest are degree, closeness, two-step reach centrality, and connectivity index (created through PCA from various centrality scores). The more central the person's household is, the more likely he/she can actively search for and utilize the information for decisions, including farming. Also, because these people can communicate and interact with more people (i.e., more sources of information), their behavior is likely to be more open to scientific knowledge. Being at the center of social networks suggests having more opportunities to make sense of good-quality information.

These network parameters are based on kinship, friendship, and work-related ties, not weather and climate information links. This was meant to reduce the simultaneity between information search and connectivity. People who are actively seeking information may forge friendships to get such. It is quite unlikely that this prevails because the element of time is larger in weather and climate information than, say, in other types of information like job opportunities or credit sources. One is unlikely to create ties to get WCI; they are more likely to get it from their existing social ties, which, in turn, may have heard it from the news over the radio.

The robustness of the model was tested through a standard process of removing and adding variables to see whether the sign and significance of other variables are sensitive to these alterations. Only those which are significant and not sensitive to these changes are considered correlates. Due to the limited sample, we used only one binary variable in the estimations (i.e., having ever availed credit). A dummy for sex was not included because it could further divide the limited sample. An iteration of the model using a male dummy yielded no significant result.

The estimation results show that few of the specified variables significantly associate with a positive outcome (Table 20). This suggests that many other unobserved factors may influence people's tendency to actively seek and utilize weather and climate information. Or perhaps things are more random. This may have something to do with the timeliness and accuracy of the information provided. For tropical cyclone warnings, although most respondents reported that such are extremely timely, a nonnegligible proportion of 44 percent found these only moderately and slightly timely. This is more problematic for heavy rainfall warnings because 63 percent thought they were only moderately and slightly timely. Note that the farm products in the study areas are extremely sensitive to the amount of rainfall. If warnings are deemed not very timely, this reduces their usefulness and relevance.

Notwithstanding the limitations of the models, the logit regression shows consistent positive and significant outcomes for network centrality, regardless of the parameter used. The more central one's household is, the higher the tendency to obtain and utilize weather and climate information, with all else being equal. Having ever availed of credit has a somewhat positive and significant association with the dependent variable.

Table 20. Logit regression results (seeking and utilizing weather and climate information)

Variable	Basic		Degree		2-Step Reach		Closeness		Connectivity Index	
Individual characteristics										
Age of head	0.2765	***	0.2694	***	0.2600	***	0.2621	***	0.2696	***
Age of head, squared	-0.0035	***	-0.0035	***	-0.0034	***	-0.0035	***	-0.0036	***
Years of education	0.0235		0.0276		0.0155		0.0175		0.0206	
Years in farming	0.0636	***	0.0674	***	0.0646	***	0.0662	***	0.0684	***
Household characteristics										
Number of household members	0.0208		0.0104		0.0009		-0.0009		0.0097	
Ever availed credit	0.5850	*	0.5348	*	0.4556		0.4390		0.5555	*
Number of smartphones	0.1741		0.1643		0.2024		0.1963		0.1841	
Asset index	-0.3033	*	-0.2550		-0.2222		-0.2162		-0.2453	
Number of vehicles owned	0.0138		-0.0819		-0.0985		-0.1257		-0.1120	
Distance to place frequented (km)	0.0103		0.0134		0.0142		0.0151		0.0151	
Log of size of farm operated	-0.0315		-0.0399		-0.0574		-0.0557		-0.0570	
Degree			4.6046	*						
2-Step reach					1.9924	**				
Closeness							6.7316	***		
Connectivity index									0.1811	**
Constant	-7.2939	***	-7.4458	***	-7.5623	***	-9.2658	***	-6.9497	***
Pseudo-R2	0.1210		0.1336		0.1405		0.1454		0.1433	
N	369		369		369		369		369	

R2 = R-squared; N = Number of observations
* $p<.05$; ** $p<.01$; *** $p<.001$
Source: Authors' computations based on primary data

The proxy indicators for skills and experience are highly significant. Age, in particular, has an inverse-U association with the probability of obtaining and utilizing WCI, while years spent in farming also have a positive correlation. Aside from these, no other variable is shown to associate significantly with the dependent variable.

Interaction with government extension workers, participation in LGU meetings, and attendance in farming schools

The survey results about people's interaction with local government extension workers indicate that there is room for improvement in the extent of farmers' exposure to AEW, who can deliver important information and opportunities. None of the respondents can identify any social relationship with an extension worker. The majority (66%) of the 353 respondents engaged in farming reported not having interacted with an extension worker in Atok or attending any meeting convened by the LGU in the past year. Of those who had met an AEW, nearly half reported that their interaction happened when the AEW visited the farm or the household, while the others recalled the AEW giving a PowerPoint Presentation. Those who said that they sought the assistance of a government extension worker are close to none (only 3). This shows that people themselves do not normally go to government extension workers, so it is up to the latter to make the connection. Of those who have experienced attending an LGU meeting (67% of total respondents), 76 percent noted that they attended farm-related seminars, while the rest attended disaster preparedness meetings. Of the respondents engaged in farming, 24 percent reported attending farm field schools.

There is some evidence that extension worker penetration has been quite effective in the past, particularly in selecting people who are more central than others (see Table 21). Survey respondents who have ever met an extension worker in the past tend to have statistically higher centrality scores than those who have not encountered any. This is also the case for those who have attended farm field school. In contrast, those who have attended LGU meetings are not statistically different from those who have not attended such meetings in terms of relative position in the community.

Table 21. Mean centrality scores by type and group, all sitios

Variable		Observation	Degree	Closeness	2-Step Reach	Centrality Index
Interact with AEW	Yes	130	0.0941	0.3211	0.3665	0.4986
	No	231	0.0779	0.3057	0.3151	-0.1279
T-test (P-value)			0.0109	0.0038	0.0043	0.0032
Attend LGU meetings	Yes	157	0.0857	0.3087	0.3377	0.1836
	No	234	0.0784	0.3069	0.3177	-0.1232
T-test (P-value)			0.2246	0.7453	0.2529	0.1324
Attend farm field school	Yes	96	0.0986	0.3277	0.4015	0.7512
	No	286	0.0778	0.3045	0.3086	-0.1587
T-test (P-value)			0.0023	0.0001	0.0000	0.0001

AEW = agricultural extension worker; LGU = local government unit
Source: Authors' computations based on primary data

However, when examined in more detail at the *sitio* level, the statistically higher mean scores between those who have interacted with AEWs are only observed in Proper Paoay, which is closest to the municipality center (see Table 22). This higher average score is also observed for those who have attended LGU meetings and farm field school compared to those who have not been in the same sitio. However, the case in Macbas is different, where the attendees of LGU meetings have statistically lower centrality scores than non-attendees. The other groups are not statistically different from one another based on centrality scores. In Tulodan, the attendees of farm field school are more central than those who have not attended farm field school. Again, there are no statistically significant differences between the other groups in terms of relative position in the community networks. Therefore, there is a need to improve the penetration of extension workers and other LGU staff/officials in remote areas like Macbas and Tulodan.

To understand how AEW penetration can be improved, the spread and position of households who interacted (through at least one member) with AEW through network graphs were examined. Figure 13 shows the network of kinship and friendship by sitio. There are isolated nodes, meaning they do not share such relations with actors in the community.

Table 22. Mean centrality scores by type, group, and sitio

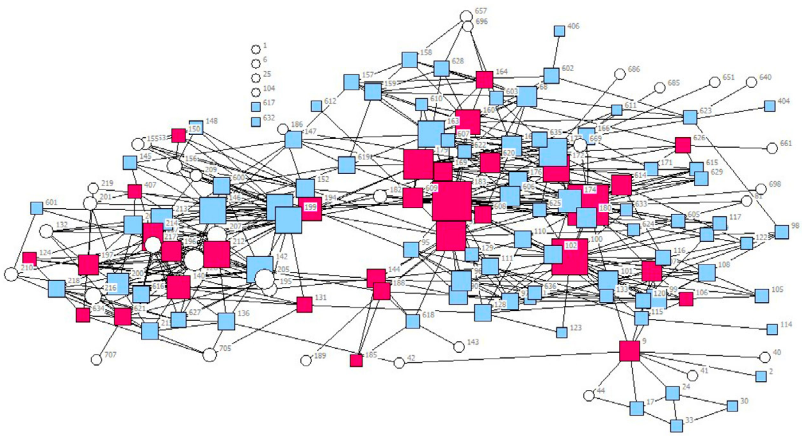
Variable		Observation	Degree	Closeness	Two-Step Reach	Centrality Index
Proper Paoay						
Interact with AEW	Yes	43	0.0965	0.3181	0.3243	0.3463
	No	132	0.0628	0.2960	0.2578	-0.6635
T-test (P-value)			0.0000	0.0046	0.0030	0.0003
Attend LGU meetings	Yes	46	0.0850	0.3122	0.3047	0.0840
	No	137	0.0649	0.2971	0.2608	-0.6215
T-test (P-value)			0.0108	0.0457	0.0446	0.0099
Attend farm field school	Yes	24	0.0835	0.3181	0.3245	0.1325
	No	159	0.0679	0.2983	0.2639	-0.5312
T-test (P-value)			0.1256	0.0409	0.0306	0.0600
Macbas						
Interact with AEW	Yes	20	0.1331	0.3195	0.4468	1.3118
	No	42	0.1299	0.3091	0.4260	1.0789
T-test (P-value)			0.8681	0.3929	0.6293	0.6869
Attend LGU meetings	Yes	40	0.0895	0.2787	0.3182	-0.1551
	No	39	0.1353	0.3106	0.4385	1.2014
T-test (P-value)			0.0064	0.0204	0.0056	0.0113
Attend farm field school	Yes	20	0.1258	0.3210	0.4565	1.1563
	No	50	0.1249	0.3024	0.4030	0.8847
T-test (P-value)			0.9639	0.1491	0.2287	0.6386

Table 22 *(continued)*

Variable		Observation	Degree	Closeness	Two-Step Reach	Centrality Index
Tulodan						
Interact with AEW	Yes	67	0.0809	0.3236	0.3696	0.3537
	No	57	0.0744	0.3255	0.3662	0.2234
T-test (P-value)			0.5130	0.8419	0.9176	0.7248
Attend LGU meetings	Yes	71	0.0840	0.3233	0.3700	0.4390
	No	58	0.0719	0.3275	0.3709	0.1632
T-test (P-value)			0.2156	0.6580	0.9756	0.4444
Attend farm field school	Yes	52	0.0950	0.3348	0.4159	0.8809
	No	77	0.0674	0.3187	0.3397	-0.0672
T-test (P-value)			0.0050	0.0909	0.0175	0.0087

AEW = agricultural extension worker; LGU = local government unit
Source: Authors’ computations based on primary data

Figure 13. Graph of social relations in Proper Paoay (red: with interaction with AEW in Atok), node size by degree



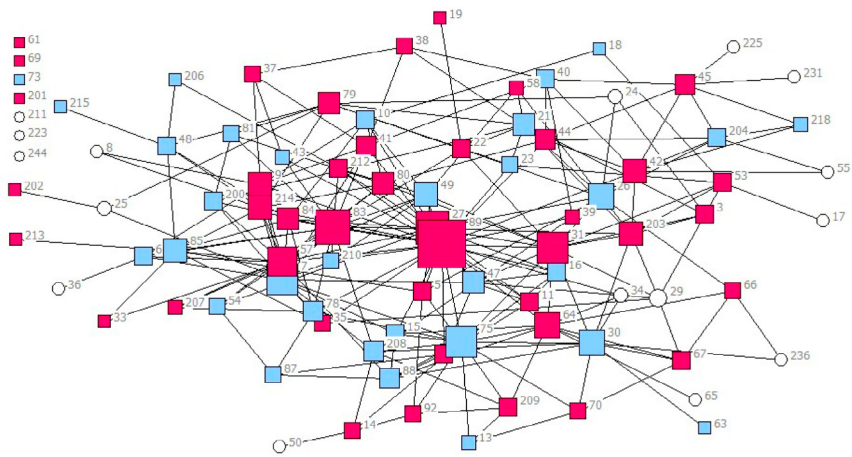
Source: Authors' illustration based on primary data

The red nodes have interacted with AEWs in the past (we call these extension workers' initial contacts), light blue ones have not, and white circle nodes are those who were not interviewed but were tagged by respondents as part of their advice network. The size of the nodes is proportional to their degree of centrality. The bigger the node, the more central it is. It would be ideal if the red nodes were also the biggest nodes, which means that AEWs have succeeded in selecting or targeting central actors in their field visits and other interaction. It would also be ideal to see red nodes scattered throughout the network, which means the selection is made in an even manner so that using them as information hubs will likely reach a wider segment of the population, all else being equal.

For Proper Paoay, regardless of whether AEWs intentionally target central actors, the initial groundwork has been quite effective because AEWs have already been in touch with more central actors in the area, as shown in Figure 13. If we focus on the biggest nodes, many are red. The graph also shows that red is prominent in most network parts. At least, these are not concentrated in a particular segment of the graph. Therefore, the AEW penetration in Proper Paoay appears to have been effective as far as the criteria mentioned above are concerned. Accordingly, the work must proceed by encouraging these individuals to serve as extension aides or social influencers in disseminating information to other actors, particularly the peripheral ones. A good complementary strategy is to assign local information hubs among those in the periphery and have LGUs monitor these hubs frequently.

Meanwhile, in Tulodan (Figure 14), it appears that they have worked with more peripheral actors than Proper Paoay. The isolated red nodes and red pendants (the nodes connected to the graph through just one link) illustrate this. Some red nodes are relatively bigger, suggesting the LGU has targeted some central actors. However, it is noticeable that the big reds are not necessarily bigger than the big light blue dots, although there is certainly more even spread of the red in this graph than in Proper Paoay. This means that AEWs may not have succeeded in making initial contact with central nodes, but the promising part is that the spread of households covered by AEWs is relatively dispersed. These households can therefore be good candidates for social influencers in the area.

Figure 14. Social relations in Tulodan (red: with interaction with AEW in Atok; node size by degree)



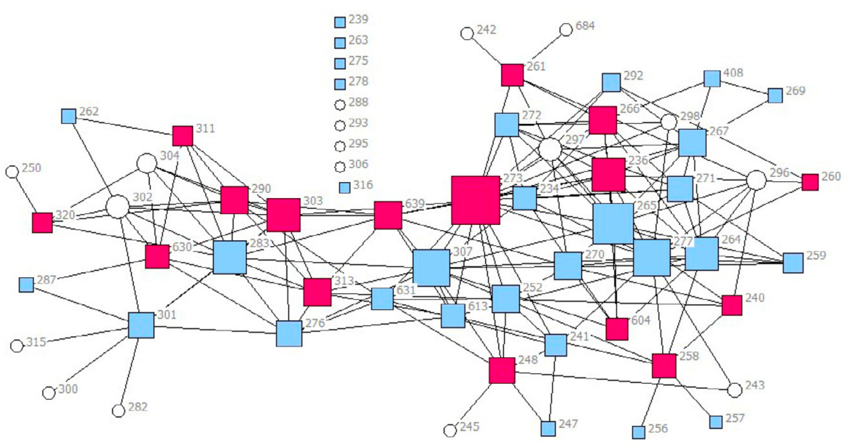
Source: Authors' illustration based on primary data

In Macbas (Figure 15), the graph shows that some red nodes are quite well-connected, as demonstrated by their bigger sizes. It, however, shows that most of these households are directly linked to one another, as shown by the red nodes sitting in some distinct segments, while some parts of the network do not have red nodes among them. Perhaps because

Macbas is very remote, farm visits may have been done in pockets of related households. This points to the need for a more representative approach in conducting farm visits, presentations, and meetings by government extension workers. AEWs can improve their work by identifying the central actors in those segments and encouraging them to echo the information they obtained. It can also be observed that some initial contacts are located at the periphery, which is promising because these can serve as hubs in their areas. This is better than not having any red among the nodes located at the periphery. Hence, the worst that we can expect, apart from not seeing any red in the graphs, is if the reds are mostly the smallest nodes. Thus, they are not good candidates for relaying information, as they have few connections. It can also be observed that AEWs need to work harder in Macbas to reach the isolated nodes.

These visual analyses have enriched our understanding by showing the de-facto outcome of AEWs' efforts to reach the households in the area. They are instrumental in devising relevant strategies for improving AEWs' penetration. Apart from the abovementioned insights that emanated from the visual appreciation of the overall networks, some points can be deduced by examining gender dimensions.

Figure 15. Social relations in Macbas (red: with interaction with AEW in Atok; node size by degree)

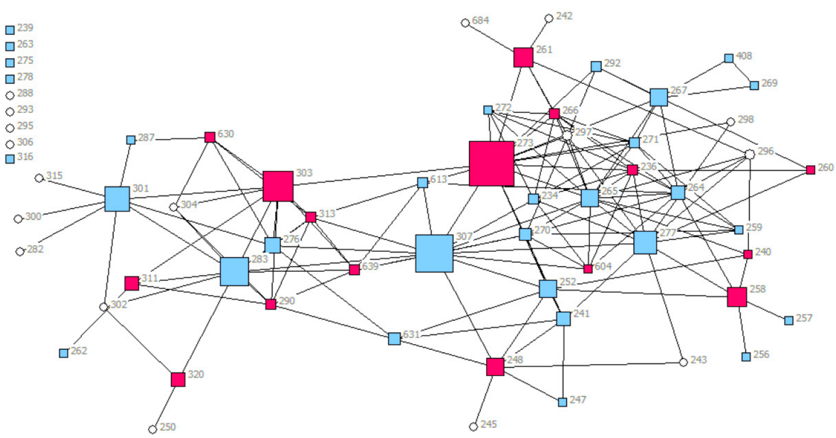


Source: Authors' illustration based on primary data

Figures 16 and 17 used betweenness to identify the central households because this parameter has wider variations across the nodes. Figure 16 shows male and female respondents' peer advice and resource network. The nodes represent households, while their connections are defined by the farm-related advice and resources they share. The AEW penetration based on the female advice network (see Figure 17) appears to be concentrated on a few related actors (see many red nodes being linked to one another and concentrating on some segments and not spread in all parts of the graph). Meanwhile, that of their male counterpart (Figure 16) appears to be more dispersed and, therefore, is a better network for information dissemination. The relatively even distribution of initial contacts of AEW presents an opportunity for reaching different actors in the network.

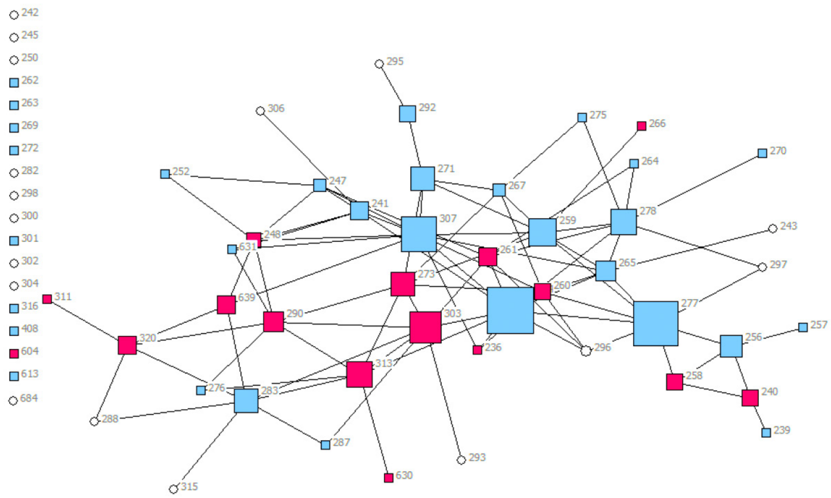
Targeting only women as the main approach may not be the most efficient. As shown in this study, targeting men may be better. Nonetheless, complementing the male-targeted approach with the female-focused one will be beneficial as the network of women seems to complement that of the men's peer advice network.

Figure 16. Advice and resource network of male respondents in Macbas node size proportional to betweenness score (red: have interacted with AEWs)



Source: Authors' illustration based on primary data

Figure 17. Advice and resource network of female respondents in Macbas node size proportional to betweenness score (red: have interacted with AEWs)



Source: Authors' illustration based on primary data

Conclusion and Recommendations

Based on the primary data gathered from Atok, Benguet, a varying extent of social cohesion, possibly based on physical context, exists. Consistent with expectations, remote communities are relatively more socially cohesive based on density and average geodesic distance. However, this study found that density is not a perfect measure of cohesion. Hence, there is a need to pay attention to isolated nodes, especially in upland rural communities. Contrary to expectations that there would be clusters, even communities near the population center can be connected, albeit with a low density. This suggests opportunities for social influencing and more fluid information dissemination.

Physical proximity and mobility are likely to be the key determinants of centrality within the community network in the context of significant geographic constraints. Central actors are those living near venues of interaction and those with greater means of transport. Peripheral ones are those who live far from these venues or those who travel far distances to market their goods and do not have means of transportation. The most affluent families are not necessarily the most central actors; these households appear on the periphery (they may find less need for social support or are too preoccupied with social interaction). It is also evident that central households occupy larger dwellings. For instance, households living near a business center like Proper Paoay include members of agricultural cooperatives and farmer organizations. Also, people from the largest clans and original settlers in the areas will likely be more centrally positioned than others.

Centrality is a significant factor in access and utilization of WCI, ceteris paribus. Therefore, enhancing social interactions and information sharing is a relevant strategy for improving access and utilization of WCI. Furthermore, this study found a differentiated reach of AEWs in communities. Efforts in areas near the capital like Proper Paoay appear promising but not quite in more remote areas like Macbas and Tulodan.

Based on the results of this study, there may be a need to craft different IEC approaches for various social and physical contexts. There is a need to promote more direct links (promote interaction) between central actors and the LGU and other information sources and producers. Encouraging activities facilitating greater and more meaningful interactions among farmers to stimulate social learning and influencing must also be explored.

For a more detailed IEC strategy, AEWs and other partners must take advantage of areas that are visited frequently by residents, as these are good candidates for convening people for information campaigns. For areas near population centers in upland communities, the more immediate concern for AEWs and other stakeholders is incentivizing initial contacts to disseminate information within their networks effectively. Due to the physical proximity of people in these areas with the municipality center, it is likely that AEWs or the LGU has already made initial contact with people with relatively strategic positions. So they can call them back if there are new programs like new technology or maybe innovation. And these people can echo the information. Afterward, close coordination with these actors can be made to reach those in the periphery.

For more remote areas, the immediate focus must be identifying central actors. Because of the remoteness of some areas, the AEWs' reach may be limited to some clusters, which could result in other segments being missed. Hence, it is important to gather participants, including the other segments that may have been overlooked in earlier efforts. Once identified, they can be incentivized to act as information hubs for their own networks. It is also important for AEWs to have more direct interaction with people in remote areas.

Meanwhile, there is a need to strengthen women's organizations, as men are normally detained on the farm while women may have more time to interact and collaborate. Likewise, it was found that improving communication capabilities and investing in mobility/transport of AEWs working in extremely challenging contexts are necessary. Also, there is an urgent need to improve access to information by enhancing the information and communications technology infrastructure in the area. For instance, mobile phone connectivity in Atok is limited, with some areas reachable only through SMS.

Different communities have different structures and social norms, and these differences must be accounted for in designing IECs and other interventions to promote social influencing and learning. Given that social network mapping is not always feasible and may not always be necessary, factors cited in this study can help understand such characteristics. IEC designs must account for social norms associated with the area's physical characteristics, socioeconomic profile, and availability and accessibility of venues of congregation or interaction.

References

Banerjee, A., A. Chandrasekhar, E. Duflo, and M. Jackson. 2013. The diffusion of microfinance. *Science* 341(6144): 363–370.

Beaman, L. and A. Dillon. 2018. Diffusion of agricultural information within social networks: Evidence on gender inequalities from Mali. *Journal of Development Economics* 133(C):147–161.

Borgatti, S.P. 2002. *NetDraw: Graph visualization software*. Lexington, KY: Analytic Technologies.

Bourdieu, P. and L.P.D. Wacquant. 1992. *An invitation to reflexive sociology*. Chicago, IL: University of Chicago Press.

Cadger, K., A. Quaicoo, E. Dawoe, and M. Isaac. 2016. Development interventions and agriculture adaptation: A social network analysis of farmer knowledge transfer in Ghana. *Agriculture* 6(32):1–15.

Google. n.d. Google Maps. https://www.google.com/maps (accessed on August 10, 2023).

Hoang, L.A., J.C. Castella, and P. Novosad. Social networks and information access: Implications for agricultural extension in a rice farming community in Northern Vietnam. *Agriculture and Human Values* 23(4):513–27.

Jackson, M.O. and B. Rogers. 2007. Relating network structure to diffusion properties through stochastic dominance. *The BE Journal of Theoretical Economics* 7(1):1–16.

Kukreja, A. and B. Chakrabarti. 2013. Agricultural knowledge management and dissemination: Initiatives by information and communication technology. *Journal of Global Communication* 6(1):51–58.

Maguire-Rajpaul, V., K. Khatun, and M.A. Hirons. 2020. Agricultural information's impact on the adaptive capacity of Ghana's smallholder cocoa farmers. https://www.frontiersin.org/articles/10.3389/fsufs.2020.00028/full (accessed on May 29, 2023).

Marsden, P.V. and N.E. Friedkin. 1994. Network studies of social influence. In *Advances in social network analysis: Research in the social and behavioral sciences*, edited by S. Wasserman and J. Galaskiewicz. Thousand Oaks, CA: SAGE Publications.

Mehta, K., A. Maretzki, and L. Semali. 2011. Trust, cellphones, social networks and agricultural entrepreneurship in East Africa: A dynamic interdependence. *African Journal of Food, Agriculture, Nutrition and Development* 11(47):5373–5388.

Meyners, J., C. Barrot, J.U. Becker, and J. Goldenberg. 2017. The role of mere closeness: How geographic proximity affects social influence. *Journal of Marketing* 81(5):49–66.

Nidumolu, U., L. Lim-Camacho, E. Gaillard, P. Hayman, and M. Howden. 2020. Linking climate forecasts to rural livelihoods: Mapping decisions, information networks and value chains. https://www.sciencedirect.com/science/article/pii/S2212094716300159 (accessed on May 29, 2023).

Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). n.d.-a. Mandate and functions. http://pagasa.dost.gov.ph/mandate-and-functions (accessed on July 19, 2021).

———. n.d.-b. Official website of PAGASA-DOST. https://www.pagasa.dost.gov.ph (accessed on August 10, 2023).

Philippine Statistics Authority (PSA). 2015. 2015 Census of Population. Quezon City, Philippines: PSA.

Pratiwi, A. and A. Suzuki. 2017. Effects of farmers' social networks on knowledge acquisition: Lessons from agricultural training in rural Indonesia. *Journal of Economic Structures* 6(1):1–23.

Ramirez, A. 2013. The influence of social networks on agricultural technology adoption. *Procedia-Social and Behavioral Sciences* 79(2013):101–116.

Spielman, D.J., K. Davis, M. Negash, and G. Ayele. 2010. Rural innovation systems and networks: Findings from a study of Ethiopian smallholders. *Agriculture and Human Values* 28(2):195–212.

Tabuga, A. 2018. The structure of origin-based social network and its influence on migration diffusion: The case of a migrant-sending village in the Philippines. PIDS Discussion Paper 2018-03. Quezon City, Philippines: Philippine Institute for Development Studies. https://pidswebs.pids.gov.ph/CDN/PUBLICATIONS/pidsdps1803.pdf (accessed on May 29, 2023).

Villanueva, A.B., R. Ogwal-Omara, Y. Jha, and E.W. Welch. 2016. Influence of social networks on the adoption of climate smart technologies in East Africa: Findings from two surveys and participatory exercises with farmers and local experts. https://www.researchgate.net/publication/306324102_Influence_of_social_networks_on_the_adoption_of_climate_smart_technologies_in_East_Africa_Findings_from_two_surveys_and_participatory_exercises_with_farmers_and_local_experts (accessed on May 29, 2023).

Wood, B.A., H.T. Blair, D.I. Gray, P.D. Kemp, P.R. Kenyon, S.T. Morris, and A.M. Sewell. 2014. Agricultural science in the wild: A social network analysis of farmer knowledge exchange. *PLoS ONE* 9(8). https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0105203 (accessed on May 29, 2023).

Wossen, T., T. Berger, T. Mequaninte, and B. Alamirew. 2013. Social network effects on the adoption of sustainable natural resource management practices in Ethiopia. *International Journal of Sustainable Development & World Ecology* 20(6):477–483.

Annexes

Table 1. List of PAGASA products and services

	Type of Information		Time Covered/Issuance	Area Covered	Description
Weather Warnings	**Tropical Cyclone/Typhoon Warnings**				
	Severe weather bulletins	Alert	12 hrs. /as need arises (11 am and 11 pm)	Nationwide	Released during events of TC passage over the Philippine Area of Responsibility (PAR)
		Warnings	3–6 hrs./as need arises (6 hourly, but 3 hourly for 24 hours before landfall)		
	Tropical cyclone warning for agriculture		24 hours/as need arises	Nationwide	24-hour Tropical Cyclone Warning Advisories (TCWA) for Agriculture activities
	Weather advisory		Once a day (11 am during heavy rainfall events)	Nationwide	Weather advisory issued during heavy rainfall events
	Heavy Rainfall and Thunderstorm Alerts				
	Rainfall warning system		3–6 hrs./as need arises	Provincial	Special report for selected areas during significant rainfall events
	Thunderstorm alert system		3–6 hrs./as need arises	Provincial	Special report for selected areas on impending thunderstorm events
	Daily Weather Forecasts				
	Weather forecasts		Daily	Nationwide	24-hour public weather forecast for specific regions (released at 5:00 am and 5:00 pm)
	Regional weather forecasts		Daily	Regional	24-hour public weather forecast (released at 5:00 am and 5:00 pm)
	Farm weather forecast and advisory		Daily	Nationwide	24-hour Farm Weather Forecast Advisory (FWFA) released at 8 am

Table 1 *(continued)*

	Type of Information	Time Covered/Issuance	Area Covered	Description
Weather Forecasts	**Biweekly and Weekly Forecasts**			
Weather Forecasts	3-day weekend agri-weather forecast	3 days/once a week	Nationwide	3-day weekend forecast for farm operations
Weather Forecasts	10-day forecast	10 days/daily	Municipal	10-day weather outlook for farm operations (temperature, rainfall, total cloud cover, relative humidity, wind) for selected municipalities
Weather Forecasts	10-day probabilistic forecast	Running 10 days/ every Thursday	Nationwide	10-day probabilistic forecast of rainfall and temperature for PAGASA synoptic station
Weather Forecasts	10-day agri-weather information	10 days/every 10th day (decadal)	Regional	10-day agri-weather forecast and crop phenology for farm operations per region
Climate Outlooks and Advisories	**Monthly Forecasts**			
Climate Outlooks and Advisories	Monthly climate assessment and outlook advisories	Monthly	Nationwide	Monthly issuance of observations for the past month and forecast for the next month include other weather systems that will likely influence the country.
Climate Outlooks and Advisories	Monthly agro-climatic review and outlook	Monthly	Nationwide	Review of the previous month and outlook of the following month's farm advisory and crop stages
Climate Outlooks and Advisories	Monthly regional forecast quick outlook	Monthly	Regional	Monthly issuance of rainfall forecast and climate outlook per region
Climate Outlooks and Advisories	Monthly tropical cyclone forecast	Monthly	Nationwide	Forecast number of tropical cyclone that will enter/occur in the PAR

Table 1 *(continued)*

	Type of Information	Time Covered/Issuance	Area Covered	Description
Climate Outlooks and Advisories	**2–6 Month Climate Forecasts**			
	Seasonal climate assessment and outlook advisories	6 months/every 6 months	Nationwide	6 months issuance of observations for the past six months and forecast for the next 6 months include other weather systems that will likely influence the country
	Monthly rainfall forecast	6 months/monthly	Nationwide	Monthly issuance of 6 months deterministic forecast for rainfall
	Monthly temperature forecast	6 months/monthly	Nationwide	Monthly issuance of 6 months deterministic forecast temperature
	Monthly Probabilistic Forecast	6 months/monthly	Nationwide	Monthly issuance of 6 months probabilistic forecast
	ENSO and Dry Spell Forecasts			
	El Niño/La Niña advisories, El Niño/La Niña watch	During the occurrence of ENSO phenomena	Nationwide	El Niño Southern Oscillation (ENSO) status; "Advisories" speak of the current ENSO phase, whereas "watch" refers to the forecast of ENSO phase based on PAGASA ENSO alert system
	Drought and dry spell assessment and forecast	As need arises	Nationwide	Issuance of drought and dry observations for the past months and forecast for the next six months, particularly during ENSO events
	Impact assessment for agriculture	Monthly	Regional	Assessment of agricultural performance based on the Generalized Monsoon Indices (GMI) and the Yield Mean Indices (YMI), and other relevant extreme weather incidents (e.g., heavy rainfall, drought, typhoon passage)

Table 1 *(continued)*

	Type of Information	Time Covered/Issuance	Area Covered	Description
Climate Outlooks and Advisories	**Narratives**			
	Press release	During a significant climate phenomena (i.e., ENSO)	Nationwide	Issued for onset and termination of: *Northeast Monsoon (*Amihan*) *Southwest Monsoon (*Habagat*) *Rainy Season Includes other climate phenomena (i.e., ENSO)
	El Niño/La Niña advisories, El Niño/La Niña watch	During the occurrence of ENSO phenomena	Nationwide	ENSO status; "Advisories" speak of the current ENSO phase, whereas "watch" refers to the forecast of the ENSO phase based on the PAGASA ENSO alert system
Climate Projections	**Climate Projections**			
	Climate projections for the Philippines	Mid-21st Century (2036–2065) Late 21st Century (2070–2099)	Nationwide; per province	Climate projections for the Philippines by province for temperature and precipitation based on all available downscaled climate change data that were simulated under three scenarios: A1B (socioeconomic-driven scenarios), RCP 4.5 and RCP 8.5 (emission-driven scenarios); and Representative Concentration Pathways (RCP)

TCWA = Tropical Cyclone Warning Advisories; TC = tropical cyclone; PAR = Philippine Area of Responsibility; FWFA = Farm Weather Forecast Advisory; PAGASA = Philippine Atmospheric, Geophysical and Astronomical Services Administration; ENSO = El Niño Southern Oscillation; GMI = Generalized Monsoon Indices; YMI = Yield Mean Indices; RCP = Representative Concentration Pathways

Source: PAGASA (n.d.-a)

Table 2. Descriptive statistics: Household head and spouse who have heard of different PAGASA products and other weather and climate information

Variable	Obs	Mean	Std. Dev.	Min	Max
Heard typhoon	363	0.99	0.12	0	1
Heard heavy rainfall	363	0.93	0.25	0	1
Heard daily forecast	363	0.88	0.32	0	1
Heard bi-weekly forecast	363	0.29	0.45	0	1
Heard monthly forecast	363	0.03	0.18	0	1
Heard 2–6 month forecast	363	0.01	0.10	0	1
Heard ENSO	363	0.89	0.32	0	1
Heard press releases	363	0.46	0.50	0	1
Heard climate projections	363	0.06	0.24	0	1
Heard indigenous forecast	363	0.30	0.46	0	1
Heard non-PAGASA info	290	0.19	0.39	0	1

Source: Authors' computations based on primary data

Table 3. Descriptive statistics: Household head and spouse who need an explanation of heard different PAGASA products and other weather and climate information

Variable	Obs	Mean	Std. Dev.	Min	Max
Need explanation typhoon	358	0.23	0.42	0	1
Need explanation heavy rainfall	338	0.19	0.39	0	1
Need explanation of daily forecast	321	0.19	0.40	0	1
Need explanation bi-weekly forecast	104	0.35	0.48	0	1
Need explanation monthly forecast	12	0.42	0.51	0	1
Need explanation 2–6 month forecast	4	0.25	0.50	0	1
Need explanation ENSO	322	0.24	0.43	0	1
Need explanation press releases	167	0.21	0.41	0	1
Need explanation climate projection	22	0.32	0.48	0	1
Need explanation indigenous forecast	109	0.12	0.33	0	1
Need explanation non-PAGASA info	104	0.14	0.35	0	1

Source: Authors' computations based on primary data

Table 4. Descriptive statistics: Household head and spouse who actively seek different PAGASA products and other weather and climate information

Variable	Obs	Mean	Std. Dev.	Min	Max
Actively seek typhoon	363	0.88	0.32	0	1
Actively seek heavy rainfall	363	0.70	0.46	0	1
Actively seek daily forecast	363	0.68	0.47	0	1
Actively seek bi-weekly forecast	363	0.17	0.38	0	1
Actively seek monthly forecast	363	0.02	0.16	0	1
Actively seek 2–6 month forecast	363	0.01	0.09	0	1
Actively seek ENSO	363	0.64	0.48	0	1
Actively seek press releases	363	0.30	0.46	0	1
Actively seek climate projection	363	0.03	0.17	0	1
Actively seek indigenous forecast	363	0.13	0.33	0	1

Source: Authors' computations based on primary data

Table 5. Descriptive statistics: Household head and spouse with access to PAGASA products and other weather and climate information

Variable	Obs	Mean	Std. Dev.	Min	Max
Access typhoon	396	0.91	0.29	0	1
Access heavy rainfall	396	0.85	0.35	0	1
Access daily forecast	396	0.81	0.39	0	1
Access bi-weekly forecast	396	0.26	0.44	0	1
Access monthly forecast	396	0.03	0.17	0	1
Access 2–6 month forecast	396	0.01	0.10	0	1
Access ENSO	396	0.82	0.39	0	1
Access press releases	396	0.42	0.49	0	1
Access climate projection	396	0.05	0.22	0	1
Access indigenous forecast	396	0.26	0.44	0	1
Access non-PAGASA info	396	0.19	0.39	0	1

Source: Authors' computations based on primary data

Table 6. Descriptive statistics: Household head's and spouse's use of different PAGASA products and other weather and climate information

Variable	Obs	Mean	Std. Dev.	Min	Max
Use in farm typhoon	396	0.80	0.40	0	1
Use in farm heavy rainfall	396	0.68	0.47	0	1
Use in farm daily forecast	396	0.63	0.48	0	1
Use in farm bi-weekly forecast	396	0.20	0.40	0	1
Use in farm monthly forecast	396	0.02	0.15	0	1
Use in farm 2–6 month forecast	396	0.01	0.09	0	1
Use in farm ENSO	396	0.66	0.47	0	1
Use in farm press releases	396	0.29	0.45	0	1
Use in farm climate projection	396	0.04	0.19	0	1
Use in farm indigenous forecast	396	0.16	0.36	0	1
Use in farm non-PAGASA info	396	0.17	0.37	0	1

Source: Authors' computations based on primary data

Table 7. Household head characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
1/0 HH male	239	0.879	0.327	0	1
HH head age as of Jan 1, 2020	236	43.152	14.384	19.023	84.019
Head civil status	238	2.004	0.798	1	5
1/0 head completed HS	236	0.466	0.500	0	1
1/0 HH head is engaged in farming	238	0.941	0.236	0	1
1/0 HH head is a member of an or	239	1	0	1	1
HH head number of years in farming	237	17.439	13.336	0	57
Number of household members	239	3.941	2.404	1	20

Source: Authors' computations based on primary data

Table 8. Household ownership of items

Variable	Obs	Mean	Std. Dev.	Min	Max
House floor area in sqm	239	107.452	156.230	0	2000
Number of radio	239	0.908	0.485	0	4
Number of TV	239	0.757	0.467	0	2
Number of landline	239	0	0	0	0
Number of basic phone	239	1.117	0.967	0	5
Number of smartphones	239	1.289	1.305	0	8
Number of computer	239	0.075	0.295	0	2
Number of refrigerator	239	0.301	0.512	0	3

Table 8 *(continued)*

Variable	Obs	Mean	Std. Dev.	Min	Max
Number of own motorcycle	239	0.176	0.461	0	4
Number of own car	239	0.456	0.833	0	5
Number of own tractor	239	0.280	0.495	0	3
Number of own water pump	239	0.397	0.507	0	2
Number of own greenhouse	239	0.264	1.030	0	8
Number of own house	239	0.996	0.394	0	3
1/0 ownership of smartphone	239	0.695	0.462	0	1
1/0 radio	239	0.845	0.362	0	1
1/0 own TV	239	0.741	0.439	0	1
1/0 basic phone	239	0.757	0.430	0	1
1/0 own vehicle	239	0.318	0.467	0	1

Source: Authors' computations based on primary data

Table 9. Credit

Variable	Obs	Mean	Std. Dev.	Min	Max
1/0 ever avail credit	232	0.491	0.501	0	1
1/0 last year avail credit	232	0.310	0.464	0	1
1/0 borrow from cooperatives	72	0.306	0.464	0	1
1/0 borrow from banks	72	0.028	0.165	0	1
1/0 borrow from private money lender	72	0.014	0.118	0	1
1/0 borrow from relatives or friends	72	0.417	0.496	0	1
1/0 borrow from landowner	72	0.014	0.118	0	1
1/0 borrow from NGOs	72	0.014	0.118	0	1
1/0 borrow from microfinance	72	0.014	0.118	0	1
1/0 borrow from input supplier	72	0.014	0.118	0	1
1/0 borrow from disposer	72	0.153	0.362	0	1

Source: Authors' computations based on primary data

Table 10. HH attendance in seminars

Variable	Obs	Mean	Std. Dev.	Min	Max
1/0 attend farmer field school	232	0.228	0.421	0	1
1/0 interact with gov agricultural extension	239	0.402	0.491	0	1
Interact by AEW visited the farm	239	0.176	0.381	0	1
Interact AEW by farmer went to AEW	239	0.013	0.112	0	1
Interact with AEW by phone online	239	0.180	0.385	0	1
AEW_online	239	0.004	0.065	0	1
1/0 HH attend LGU meeting	239	0.393	0.490	0	1
HH attend farm related seminar	239	0.301	0.460	0	1
HH attend disaster preparedness	239	0.117	0.322	0	1
HH attend FDS related	239	0.079	0.271	0	1
1/0 HH head interacts with private technician	192	0.698	0.460	0	1
1/0 HH head private tech visits farm	158	0.633	0.483	0	1
1/0 HH head attend mtg or private ppt	104	0.442	0.499	0	1
1/0 HH head private interact online	1	1	–	1	1
1/5 household adopt technology (1 – very unlikely to 5 – definitely)	232	3.978	1.055	1	5

Source: Authors' computations based on primary data

Table 11. Sources of information by weather and climate information by type

A. Descriptive statistics: Sources of typhoon information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	359	0.10	0.30	0	1
Internet	359	0.20	0.40	0	1
Radio	359	0.87	0.33	0	1
Television	359	0.76	0.43	0	1
Broadsheet	359	0	0.05	0	1
Tabloid	359	0	0	0	0
Extension worker	359	0.01	0.09	0	1
PAGASA	359	0	0	0	0
Self	359	0.01	0.09	0	1
Other person	359	0.26	0.44	0	1
NDRRMC	359	0.23	0.42	0	1

Source: Authors' computations based on primary data

Table 11 *(continued)*

B. Descriptive statistics: Sources of heavy rainfall information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	338	0.01	0.11	0	1
Internet	338	0.11	0.32	0	1
Radio	338	0.77	0.42	0	1
Television	338	0.76	0.43	0	1
Broadsheet	338	0	0	0	0
Tabloid	338	0	0	0	0
Extension worker	338	0	0.05	0	1
PAGASA	338	0	0	0	0
Self	338	0	0.05	0	1
Other person	338	0.12	0.33	0	1
NDRRMC	338	0.01	0.08	0	1

Source: Authors' computations based on primary data

C. Descriptive statistics: Sources of daily forecast information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	320	0.01	0.11	0	1
Internet	320	0.04	0.20	0	1
Radio	320	0.77	0.42	0	1
Television	320	0.66	0.48	0	1
Broadsheet	320	0	0	0	0
Tabloid	320	0	0	0	0
Extension worker	320	0	0	0	0
PAGASA	320	0	0	0	0
Self	320	0	0	0	0
Other person	320	0.06	0.24	0	1
NDRRMC	320	0	0	0	0

Source: Authors' computations based on primary data

Table 11 *(continued)*

D. Descriptive statistics: Sources of bi-weekly forecast information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	104	0	0	0	0
Internet	104	0.07	0.25	0	1
Radio	104	0.48	0.50	0	1
Television	104	0.76	0.43	0	1
Broadsheet	104	0	0	0	0
Tabloid	104	0	0	0	0
Extension worker	104	0	0	0	0
PAGASA	104	0	0	0	0
Self	104	0	0	0	0
Other person	104	0.06	0.23	0	1
NDRRMC	104	0	0	0	0

Source: Authors' computations based on primary data

E. Descriptive statistics: Sources of monthly forecast information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	12	0.08	0.29	0	1
Internet	12	0.17	0.39	0	1
Radio	12	0.92	0.29	0	1
Television	12	0.75	0.45	0	1
Broadsheet	12	0	0	0	0
Tabloid	12	0	0	0	0
Extension worker	12	0	0	0	0
PAGASA	12	0	0	0	0
Self	12	0	0	0	0
Other person	12	0.08	0.29	0	1
NDRRMC	12	0	0	0	0

Source: Authors' computations based on primary data

Table 11 *(continued)*

F. Descriptive statistics: Sources of 2–6-month forecast information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	4	0	0	0	0
Internet	4	0.25	0.50	0	1
Radio	4	0.75	0.50	0	1
Television	4	1	0	1	1
Broadsheet	4	0	0	0	0
Tabloid	4	0	0	0	0
Extension worker	4	0	0	0	0
PAGASA	4	0	0	0	0
Self	4	0	0	0	0
Other person	4	0	0	0	0
NDRRMC	4	0	0	0	0

Source: Authors' computations based on primary data

G. Descriptive Statistics: Sources of ENSO forecast information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	323	0	0	0	0
Internet	323	0.10	0.30	0	1
Radio	323	0.76	0.43	0	1
Television	323	0.80	0.40	0	1
Broadsheet	323	0	0	0	0
Tabloid	323	0	0	0	0
Extension worker	323	0	0.06	0	1
PAGASA	323	0	0	0	0
Self	323	0	0.06	0	1
Other persons	323	0.06	0.23	0	1
NDRRMC	323	0	0	0	0

Source: Authors' computations based on primary data

Table 11 *(continued)*

H. Descriptive statistics: Sources of press release information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	168	0	0	0	0
Internet	168	0.02	0.15	0	1
Radio	168	0.72	0.45	0	1
Television	168	0.75	0.43	0	1
Broadsheet	168	0	0	0	0
Tabloid	168	0	0	0	0
Extension worker	168	0	0	0	0
PAGASA	168	0	0	0	0
Self	168	0.01	0.11	0	1
Other persons	168	0.05	0.23	0	1
NDRRMC	168	0	0	0	0

Source: Authors' computations based on primary data

I. Descriptive statistics: Sources of climate projections information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	21	0	0	0	0
Internet	21	0.05	0.22	0	1
Radio	21	0.57	0.51	0	1
Television	21	0.71	0.46	0	1
Broadsheet	21	0	0	0	0
Tabloid	21	0	0	0	0
Extension worker	21	0.05	0.22	0	1
PAGASA	21	0	0	0	0
Self	21	0.05	0.22	0	1
Other person	21	0.05	0.22	0	1
NDRRMC	21	0	0	0	0

Source: Authors' computations based on primary data

Table 11 *(continued)*

J. Descriptive statistics: Sources of indigenous forecast information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	104	0.01	0.10	0	1
Internet	104	0	0	0	0
Radio	104	0.05	0.21	0	1
Television	104	0.04	0.19	0	1
Broadsheet	104	0	0	0	0
Tabloid	104	0	0	0	0
Extension worker	104	0.15	0.36	0	1
PAGASA	104	0	0	0	0
Self	104	0.71	0.46	0	1
Other person	104	0.40	0.49	0	1
NDRRMC	104	0	0	0	0

Source: Authors' computations based on primary data

K. Descriptive statistics: Sources of non-PAGASA information

Variable	Obs	Mean	Std. Dev.	Min	Max
SMS	76	0	0	0	0
Internet	76	0.11	0.31	0	1
Radio	76	0.83	0.38	0	1
Television	76	0.67	0.47	0	1
Broadsheet	76	0	0	0	0
Tabloid	76	0	0	0	0
Extension worker	76	0	0	0	0
PAGASA	76	0	0	0	0
Self	76	0	0	0	0
Other person	76	0.03	0.16	0	1
NDRRMC	76	0	0	0	0

Source: Authors' computations based on primary data

Table 12. Summary statistics of variables used in the regression analyses

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
Individual characteristics					
Searched for and utilized all four major types of WCI	388	0.3273	0.4698	0.0000	1.0000
Age of head	388	42.21890	14.0154	14.4914	84.0192
Age of head, squared	388	1978.3590	1295.4240	210.0018	7059.2210
Years of education	378	8.6481	3.4319	0.0000	16.0000
Years in farming	384	15.8542	13.0524	0.0000	57.0000
Household characteristics					
Number of household members	388	4.0902	2.2641	1.0000	20.0000
Ever availed credit	375	0.5013	0.5007	0.0000	1.0000
Number of smartphones	388	1.2500	1.2563	0.0000	8.0000
Asset index	381	0.0282	1.3154	-1.6128	4.4973
Number of vehicles owned	388	0.4923	0.8848	0.0000	5.0000
Distance to place frequented by respondent (km)	388	3.7586	12.5776	0.0000	120.0000
Log of size of farm operated	388	0.1825	1.9974	-3.9120	6.6846
Degree	381	0.0991	0.0694	0.0060	0.4260
Two-step reach	381	0.4589	0.2071	0.0390	0.9330
Closeness	381	0.3874	0.0688	0.2250	0.5980
Connectivity index	381	0.1640	2.3966	-4.6117	8.8381

WCI = Weather and climate information; km= kilometer
Source: Authors' computations based on primary data

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Social norms and structures are vital factors that shape people's behavior and attitudes. Therefore, analyzing such underlying forces in creating strategies to influence behavior and activities is useful. Agricultural extension services, such as information dissemination and farmers' training, are some of the interventions that can benefit from such analyses, especially within a context of limited human and financial resources. The lessons learned from analyzing social networks and norms can be used to identify potential local knowledge and information disseminators, thereby aiding the extension services. It also helps in formulating more contextualized approaches to reach the underserved and hard-to-reach areas. Applying this approach, this study used the case of a remote upland area in Atok, Benguet, a major vegetable producer. A social network analysis was used to develop insights for designing more effective extension strategies. The results show that interventions like information and education campaigns can be improved by acknowledging the nuances in social relation structures.

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